Reflections on Framing and Making Decisions in the Face of Uncertainty

International Conference on Uncertainty in Risk Analysis
Berlin, Germany – 2019 February 20-22

M. Granger Morgan
Hamerschlag Professor of Engineering
Department of Engineering and Public Policy
Carnegie Mellon University
tel: 412-268-2672
e-mail: granger.morgan@andrew.cmu.edu

Almost all important decisions…

…involve considerable uncertainty.

At a personal level:

- Where to go to college
- Who to marry
- When and whether to have kids

In a company or other organization:

- Who to hire
- What products to develop

In a nation:

- How best to structure taxes
- How best to deal with social services & health care
- When to go to war
- When to sue for peace

In this talk I will:

- Discuss *prescriptive* analytical strategies that suggest how people *should* frame and make decisions in the face of uncertainty.
  - Decision rules
  - Benefit-cost analysis
  - Decision analysis
  - Multi-criteria analysis
  - Real options
  - Bounding analysis
- Discuss how people *actually* frame and make decisions in the face of uncertainty.
  - Cognitive heuristics
  - Ubiquitous overconfidence
  - The need to be quantitative
  - Methods for formal quantitative expert elicitation
  - Problems with the use of scenarios
  - Two comments about integrated assessment.

As I go through these I will briefly mention of some relevant literatures.

Decision Rules

Binary or threshold

Safe/Unsafe; Regulate/Don't regulate; etc.

In the U.S. in addition to chemical risk assessment we have the example of the Clean Air Act which adopts a "rights based" formulation – "choose a level that protects the most sensitive population."

Balancing

Benefit-Cost; Maximize (expected) Net Benefits; etc.

In the U.S. many federal water quality rules are *not* rights based. They call for a balance between water quality and control costs.

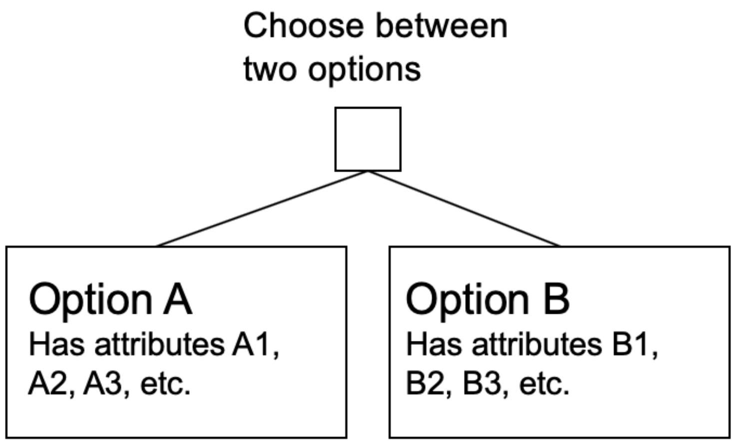
Avoid extremes

Minimize the chance of the worst outcomes, etc.

Most of the classic literature on decision making focuses on maximizing (expected) net benefits.

Benefit-cost analysis

Suppose I have two feasible options in which I could invest to achieve some desired end.



What strategy should I adopt in making my choice?

I could choose the one that is:

- Most energy efficient
- The one with the best engineering
- The one that increases entropy the least
- The one that wins in a survey of consumer preferences
- The one favored by the Environmental Defense Fund
- The one favored by the U.S. OMB
- Choose the simplest
- Choose the cheapest (relative effectiveness)

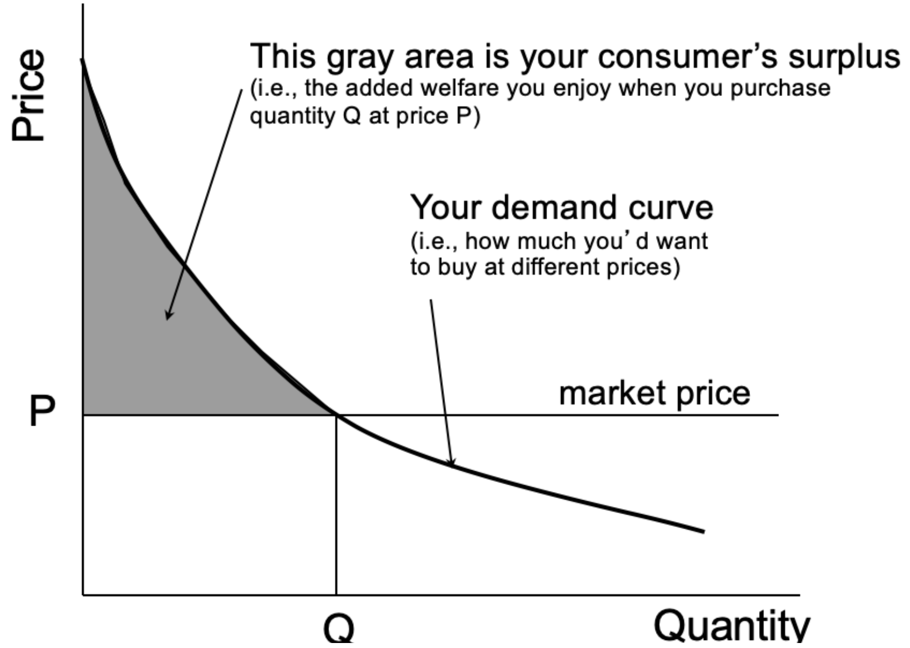
Benefit-cost analysis says choose the one with the highest net benefit:

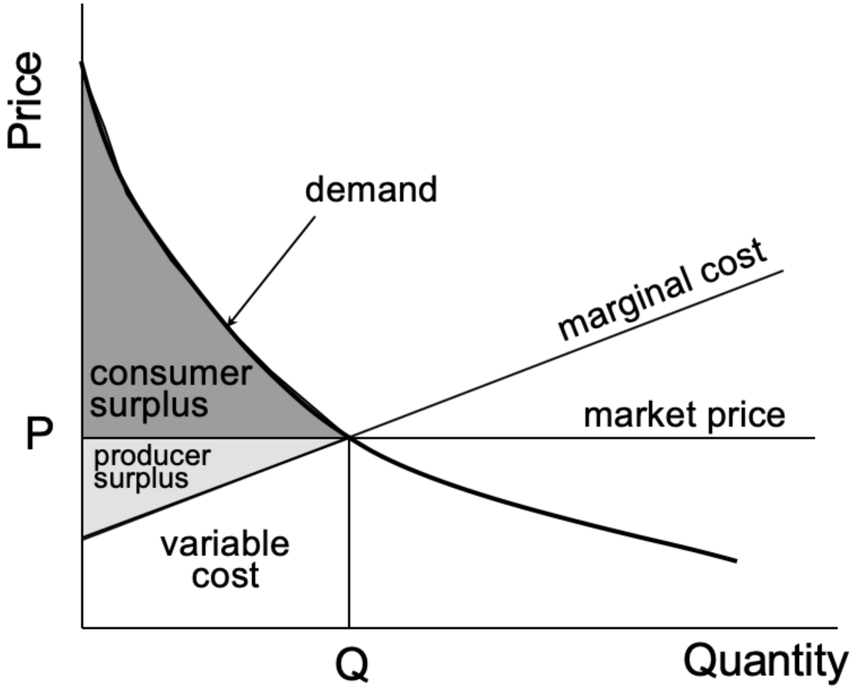
$$\sum_{j=1}^{N} B_j - \sum_{k=1}^{M} C_k$$

That sounds simple…

…but the details of how to perform a B-C analysis can get very complicated.

For example, one standard strategy to estimate benefits is to estimate "consumer surplus."



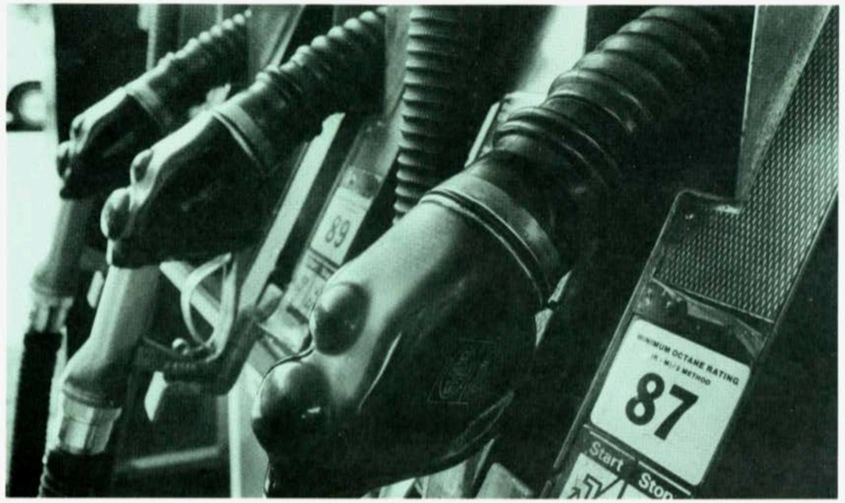


An example:

Lester B. Lave et al., "Controlling Emissions from Motor Vehicles: A benefit-cost analysis of vehicle emission control alternatives," *Environmental Science & Technology*, *24*(8), pp. 1128-1135, August 1990.

Controlling emissions from motor vehicles

A benefit–cost analysis of vehicle emission control alternatives



Lester B. Lave
Carnegie Mellon University
Pittsburgh, PA 15213

William E. Wecker
Winthrop S. Reis
Duncan A. Ross
William E. Wecker Associates
Novato, CA 94945

U.S. ozone levels exceed the National Ambient Air Quality Standard (NAAQS) of 0.12 ppm in virtually every major urban area and in many nonurban areas in the East *(1)*. Hydrocarbon emissions are a primary contributor to the photochemical reactions that produce ozone *(2)*. These emissions from cars and light duty trucks (LDTs) account for approximately 35% of total man-made hydrocarbon emissions *(1)*.

This article reports the results of a benefit–cost analysis of alternative strategies for controlling emissions from hydrocarbon refueling and evaporative emissions from cars and LDTs. Our analysis accounts for interactions among the different control methods that influence both the costs and benefits of the available strategies. It also examines the role played by variations in temperature conditions and pollution levels across regions and seasons in estimating the costs and benefits. (A detailed report of the analysis is available from the authors.)

We have found that the most economically efficient control of refueling and evaporative hydrocarbon emissions from cars and LDTs would result from a mixed strategy that includes fuel volatility controls and controls on service station pumps. The most cost-effective control strategy involves fuel volatility and gasoline pump controls, which can be tailored to each region; the former can be changed with each season. Such flexible controls can be targeted to the specific regions and season where they will do the most good, while avoiding the wasteful cost of controls when and where ozone is not a problem. Vehicle-based controls do not have these advantages.

Sources of emissions

In a vehicle's fuel system, gasoline may be heated and vaporized by diurnal ambient temperature deviations (excursions) as well as by the engine and exhaust system after the engine is turned off ("hot soak") or when it is operated under extreme conditions ("running loss") *(3)*. Evaporative emissions occur when the amount of gasoline vapors exceeds the capacity of the vehicle's emission control system.

Refueling emissions occur primarily when liquid fuel from the gas pump displaces the vapor in the fuel tank. These vapors escape through the vehicle fuel tank fillpipe. A secondary source of refueling emissions is the escape of vapor from the service station's underground fuel tank. When liquid fuel is pumped from the underground tank, it is replaced by outside air. The increased concentration of air reduces the partial pressure of the gasoline vapor in the tank. More gasoline evaporates to return the liquid–vapor system in the underground tank to equilibrium. The

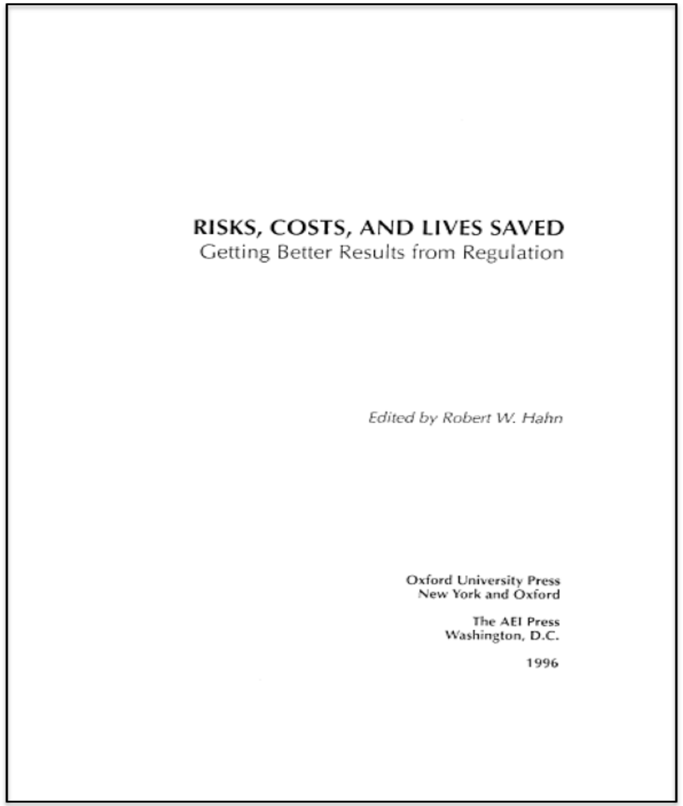
0013-936X/90/0924-1128$02.50/0

While there is no reason…

…that it *can't* incorporate uncertainty, most B-C analysis has included little or no characterization or analysis of uncertainty.

The best critical assessment I know of B-C analysis was written by Lester, who was one of the method's leading practitioners.

Lester B. Lave, "Benefit-Cost Analysis: Do the benefits exceed the costs?" from *Risks Costs and Lives Saved: Getting better results from regulation,* Robert Hahn (ed.), Oxford, 1996, pp. 104-134.



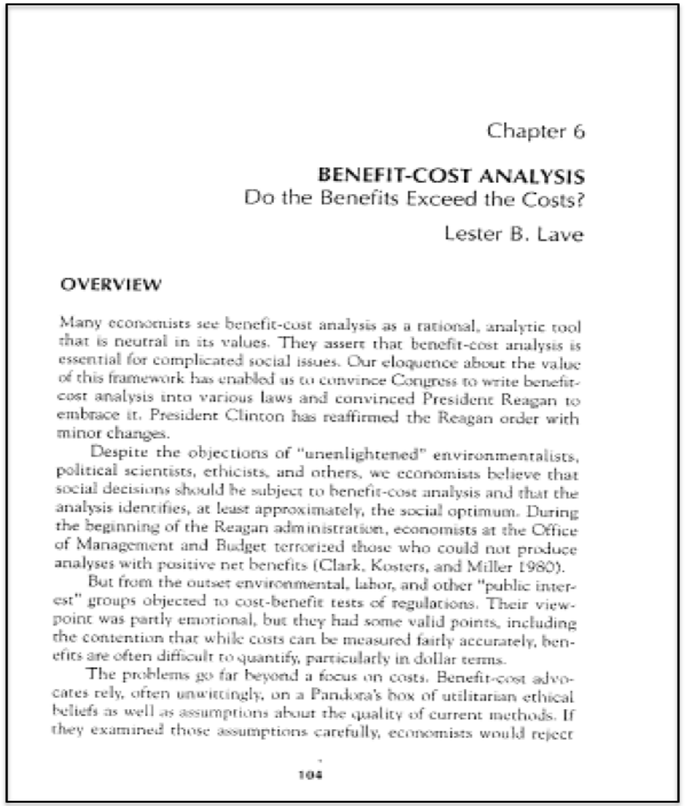
RISKS, COSTS, AND LIVES SAVED
Getting Better Results from Regulation

Edited by Robert W. Hahn

Oxford University Press
New York and Oxford

The AEI Press
Washington, D.C.

1996



Chapter 6

BENEFIT-COST ANALYSIS
Do the Benefits Exceed the Costs?

Lester B. Lave

OVERVIEW

Many economists see benefit-cost analysis as a rational, analytic tool that is neutral in its values. They assert that benefit-cost analysis is essential for complicated social issues. Our eloquence about the value of this framework has enabled us to convince Congress to write benefit-cost analysis into various laws and convinced President Reagan to embrace it. President Clinton has reaffirmed the Reagan order with minor changes.

Despite the objections of "unenlightened" environmentalists, political scientists, ethicists, and others, we economists believe that social decisions should be subject to benefit-cost analysis and that the analysis identifies, at least approximately, the social optimum. During the beginning of the Reagan administration, economists at the Office of Management and Budget terrorized those who could not produce analyses with positive net benefits (Clark, Kosters, and Miller 1980).

But from the outset environmental, labor, and other "public interest" groups objected to cost-benefit tests of regulations. Their viewpoint was partly emotional, but they had some valid points, including the contention that while costs can be measured fairly accurately, benefits are often difficult to quantify, particularly in dollar terms.

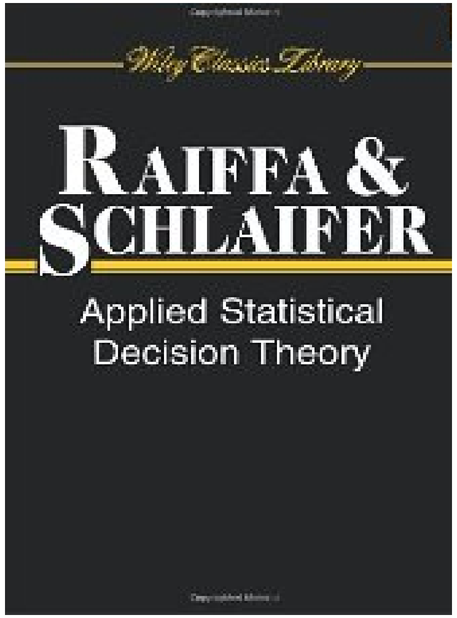
The problems go far beyond a focus on costs. Benefit-cost advocates rely, often unwittingly, on a Pandora's box of utilitarian ethical beliefs as well as assumptions about the quality of current methods. If they examined those assumptions carefully, economists would reject

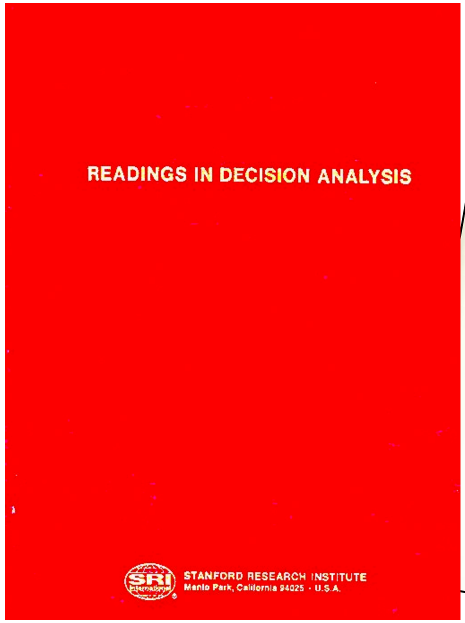
104

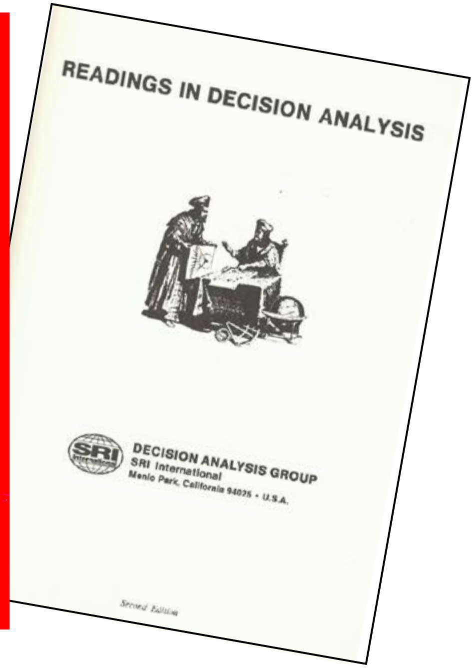
The fact that there is uncertainty…

…should not by itself be grounds for inaction. Indeed, the consequences of doing nothing often carry comparable or larger uncertainty.

There is a large literature on analytical strategies for framing and making decisions in the face of uncertainty.







The methods they developed are now termed Decision Analysis

Identify a set of choices with outcomes *x.*

For each choice, use all available current knowledge *c* to assess the probability that each of the outcomes *x* will occur. That is, assess $p(x|c)$.

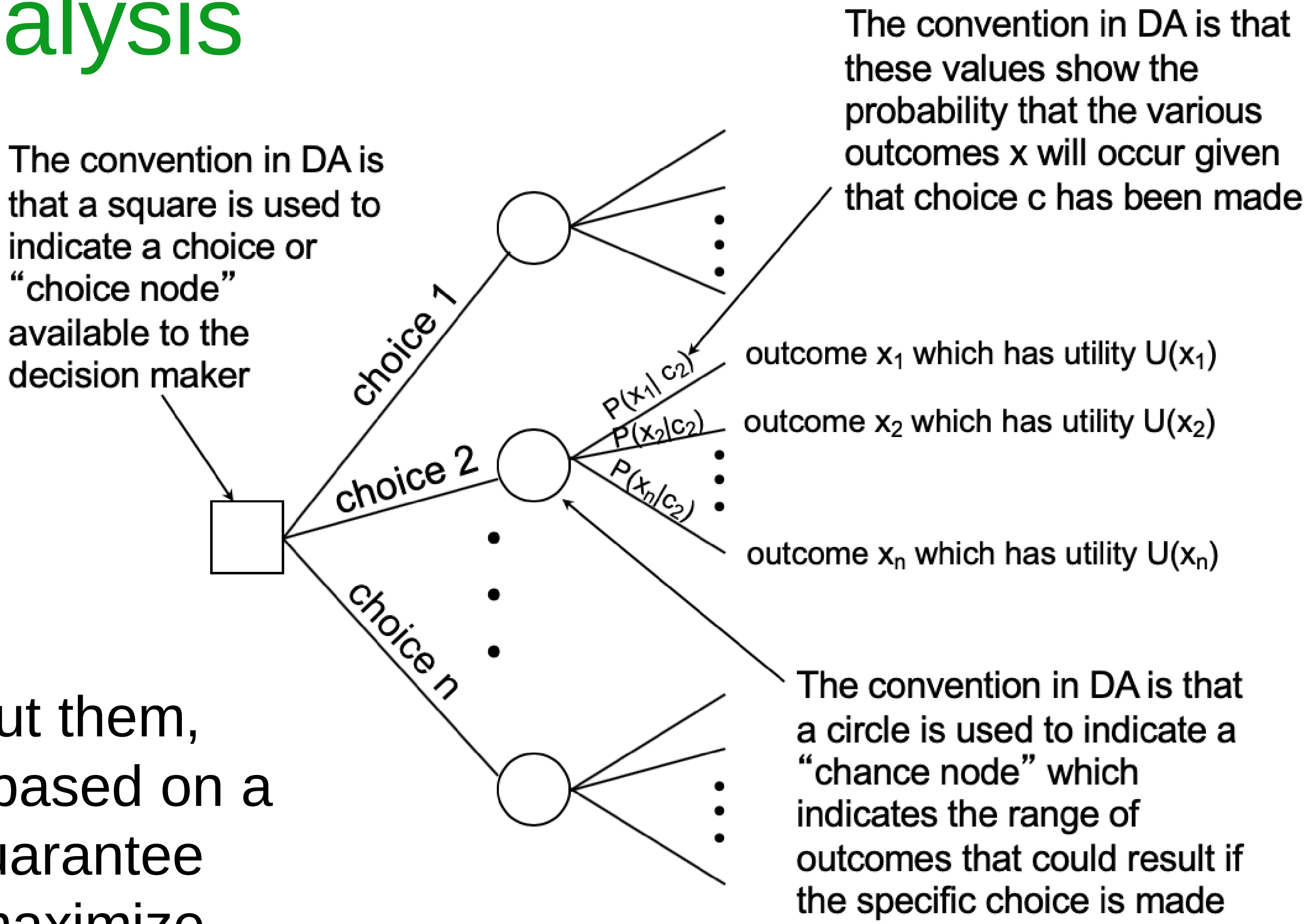
Decide how you value each of those outcomes.
That is, assess your "utility function" $U(x)$

Make the choice that will maximize your expected utility. That is:

$$\mathrm{Max}[\int p(x|c)\, U(x)\, dx]$$

Rather than deal with continuous functions DA typically discretizes everything.

Decision Analysis



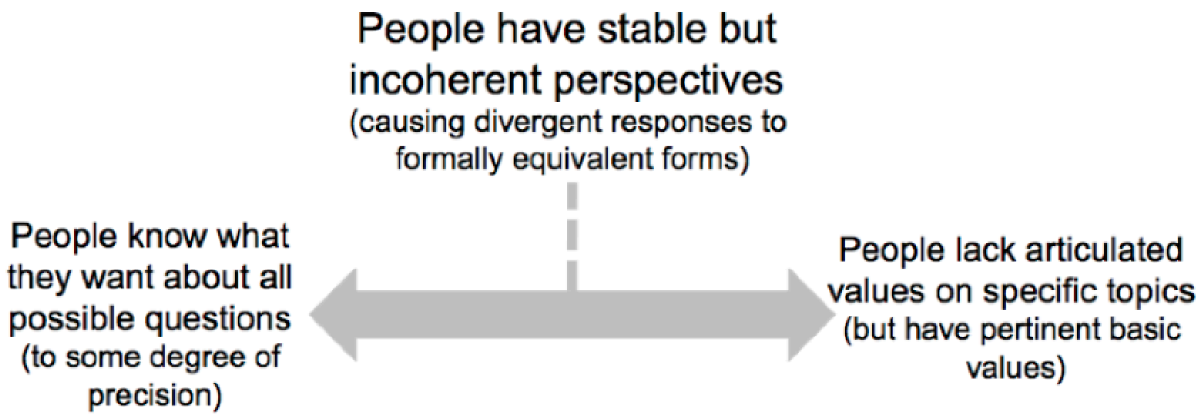
While I will not take time to talk about them, decision analysis is based on a set of axioms that guarantee that the choice will maximize your expected utility.

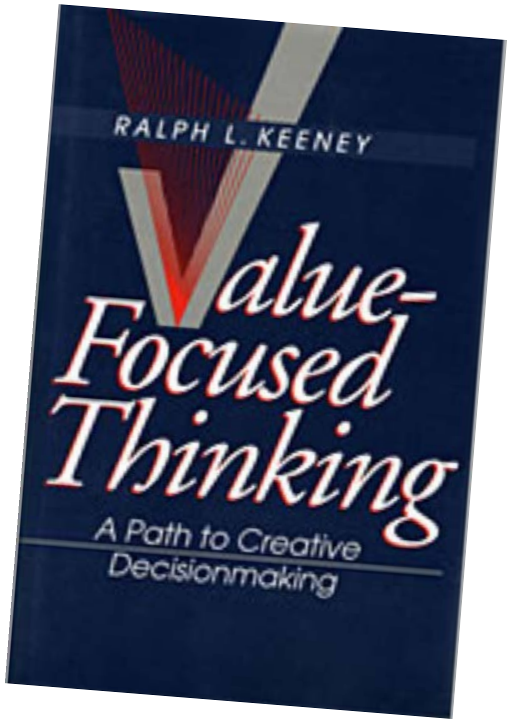
To do a decision analysis one needs to know the decision maker’s preferences

Many economists operate with the assumption that we all have well articulated utility functions in our heads, so the issue is just how best to observe U(*x*).

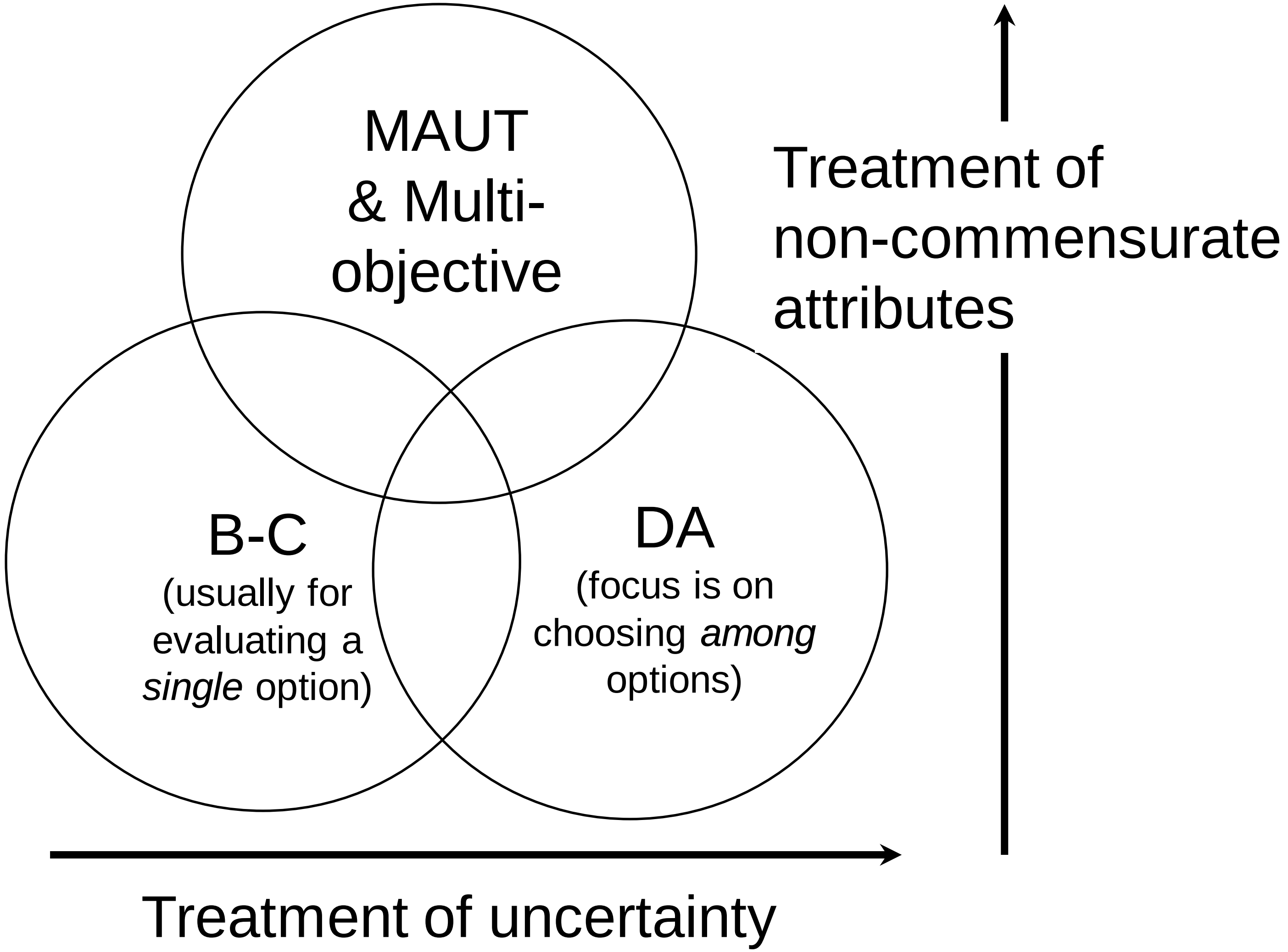
Psychologists and decision analysts believe people often need help in figuring our their preferences.

Fischhoff (1991) lays out this continuum of possibilities.

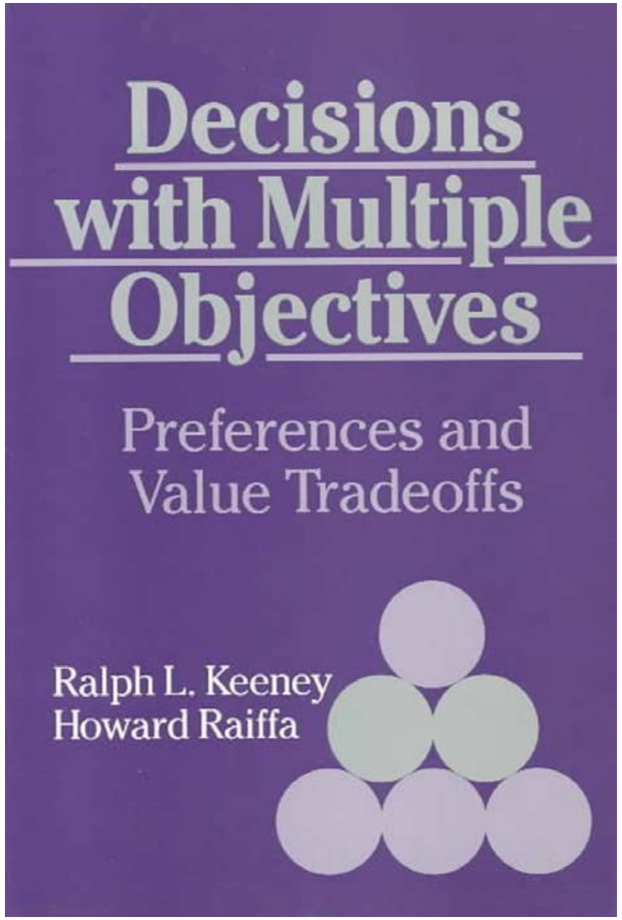


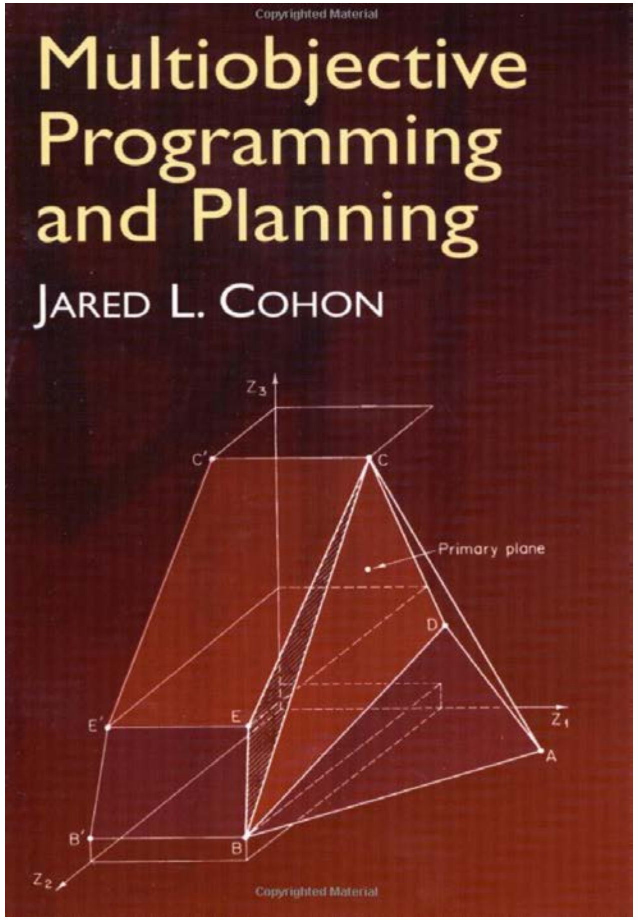


A simple taxonomy of analytical methods



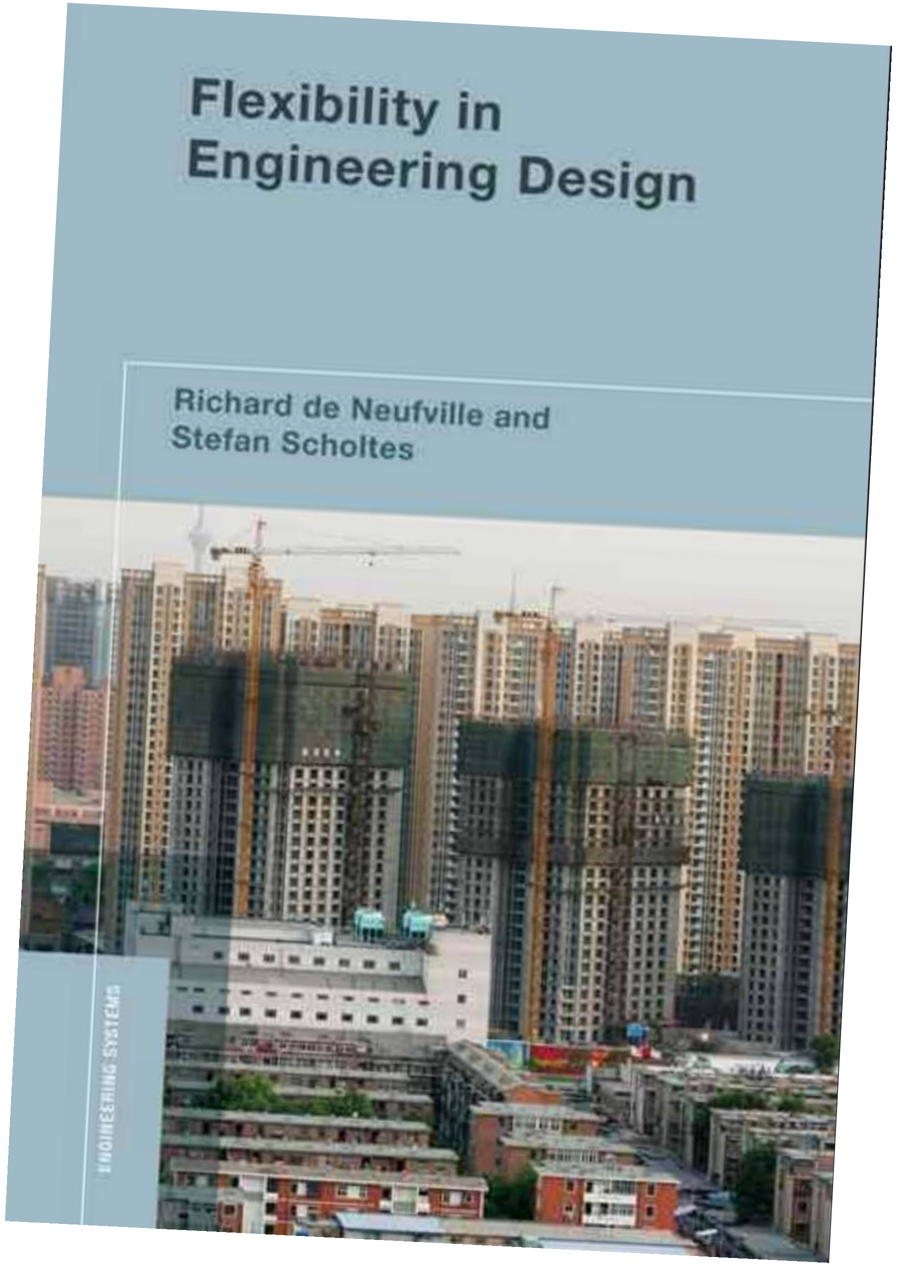
Dealing with multiple objectives





One other strategy

The use of real options as an alternative to net present value can and better address uncertain future contingencies.



Bounding Analysis

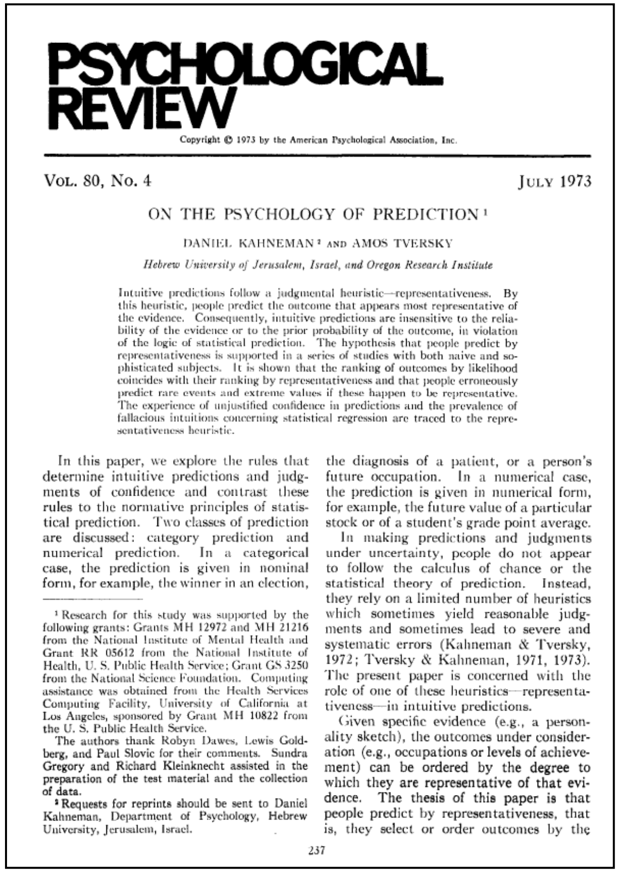
While there has been no mention of this approache in the talks we have heard, sometimes the best we can (or should) do, is to use order of magnitude methods to set bounds.

In this talk I will:

- Discuss *prescriptive* analytical strategies that suggest how people *should* frame and make decisions in the face of uncertainty.
    - Decision rules
    - Benefit-cost analysis
    - Decision analysis
    - Multi-criteria analysis
    - Real options
    - Bounding analysis
- Discuss how people *actually* frame and make decisions in the face of uncertainty.
    - Cognitive heuristics
    - Ubiquitous overconfidence
    - The need to be quantitative
    - Methods for formal quantitative expert elicitation
    - Problems with the use of scenarios
    - Two comments about integrated assessment.

There is a large literature…

…based on empirical studies, that describes how people make judgments in the face of uncertainty.



PSYCHOLOGICAL REVIEW

Copyright © 1973 by the American Psychological Association, Inc.

VOL. 80, NO. 4 JULY 1973

ON THE PSYCHOLOGY OF PREDICTION [1]

DANIEL KAHNEMAN [2] AND AMOS TVERSKY

Hebrew University of Jerusalem, Israel, and Oregon Research Institute

Intuitive predictions follow a judgmental heuristic—representativeness. By this heuristic, people predict the outcome that appears most representative of the evidence. Consequently, intuitive predictions are insensitive to the reliability of the evidence or to the prior probability of the outcome, in violation of the logic of statistical prediction. The hypothesis that people predict by representativeness is supported in a series of studies with both naive and sophisticated subjects. It is shown that the ranking of outcomes by likelihood coincides with their ranking by representativeness and that people erroneously predict rare events and extreme values if these happen to be representative. The experience of unjustified confidence in predictions and the prevalence of fallacious intuitions concerning statistical regression are traced to the representativeness heuristic.

In this paper, we explore the rules that determine intuitive predictions and judgments of confidence and contrast these rules to the normative principles of statistical prediction. Two classes of prediction are discussed: category prediction and numerical prediction. In a categorical case, the prediction is given in nominal form, for example, the winner in an election, the diagnosis of a patient, or a person's future occupation. In a numerical case, the prediction is given in numerical form, for example, the future value of a particular stock or of a student's grade point average.

In making predictions and judgments under uncertainty, people do not appear to follow the calculus of chance or the statistical theory of prediction. Instead, they rely on a limited number of heuristics which sometimes yield reasonable judgments and sometimes lead to severe and systematic errors (Kahneman & Tversky, 1972; Tversky & Kahneman, 1971, 1973). The present paper is concerned with the role of one of these heuristics—representativeness—in intuitive predictions.

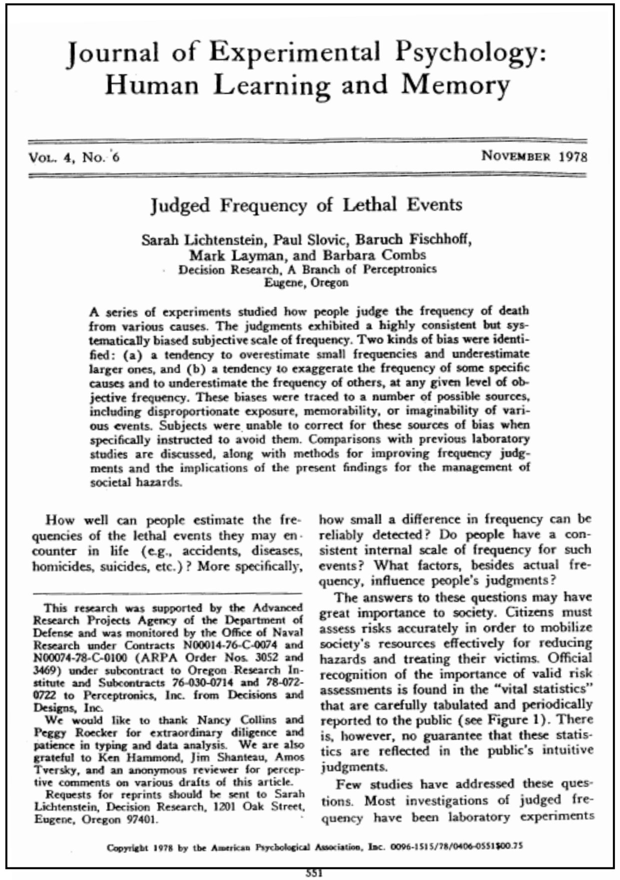
Given specific evidence (e.g., a personality sketch), the outcomes under consideration (e.g., occupations or levels of achievement) can be ordered by the degree to which they are representative of that evidence. The thesis of this paper is that people predict by representativeness, that is, they select or order outcomes by the

[1] Research for this study was supported by the following grants: Grants MH 12972 and MH 21216 from the National Institute of Mental Health and Grant RR 05612 from the National Institute of Health, U. S. Public Health Service; Grant GS 3250 from the National Science Foundation. Computing assistance was obtained from the Health Services Computing Facility, University of California at Los Angeles, sponsored by Grant MH 10822 from the U. S. Public Health Service.

The authors thank Robyn Dawes, Lewis Goldberg, and Paul Slovic for their comments. Sundra Gregory and Richard Kleinknecht assisted in the preparation of the test material and the collection of data.

[2] Requests for reprints should be sent to Daniel Kahneman, Department of Psychology, Hebrew University, Jerusalem, Israel.

237



Journal of Experimental Psychology: Human Learning and Memory

VOL. 4, NO. 6 NOVEMBER 1978

Judged Frequency of Lethal Events

Sarah Lichtenstein, Paul Slovic, Baruch Fischhoff, Mark Layman, and Barbara Combs
Decision Research, A Branch of Perceptronics
Eugene, Oregon

A series of experiments studied how people judge the frequency of death from various causes. The judgments exhibited a highly consistent but systematically biased subjective scale of frequency. Two kinds of bias were identified: (a) a tendency to overestimate small frequencies and underestimate larger ones, and (b) a tendency to exaggerate the frequency of some specific causes and to underestimate the frequency of others, at any given level of objective frequency. These biases were traced to a number of possible sources, including disproportionate exposure, memorability, or imaginability of various events. Subjects were unable to correct for these sources of bias when specifically instructed to avoid them. Comparisons with previous laboratory studies are discussed, along with methods for improving frequency judgments and the implications of the present findings for the management of societal hazards.

How well can people estimate the frequencies of the lethal events they may encounter in life (e.g., accidents, diseases, homicides, suicides, etc.)? More specifically, how small a difference in frequency can be reliably detected? Do people have a consistent internal scale of frequency for such events? What factors, besides actual frequency, influence people's judgments?

The answers to these questions may have great importance to society. Citizens must assess risks accurately in order to mobilize society's resources effectively for reducing hazards and treating their victims. Official recognition of the importance of valid risk assessments is found in the "vital statistics" that are carefully tabulated and periodically reported to the public (see Figure 1). There is, however, no guarantee that these statistics are reflected in the public's intuitive judgments.

Few studies have addressed these questions. Most investigations of judged frequency have been laboratory experiments

This research was supported by the Advanced Research Projects Agency of the Department of Defense and was monitored by the Office of Naval Research under Contracts N00014-76-C-0074 and N00074-78-C-0100 (ARPA Order Nos. 3052 and 3469) under subcontract to Oregon Research Institute and Subcontracts 76-030-0714 and 78-072-0722 to Perceptronics, Inc. from Decisions and Designs, Inc.

We would like to thank Nancy Collins and Peggy Roecker for extraordinary diligence and patience in typing and data analysis. We are also grateful to Ken Hammond, Jim Shanteau, Amos Tversky, and an anonymous reviewer for perceptive comments on various drafts of this article.

Requests for reprints should be sent to Sarah Lichtenstein, Decision Research, 1201 Oak Street, Eugene, Oregon 97401.

Copyright 1978 by the American Psychological Association, Inc. 0096-1515/78/0406-0551$00.75

551

Judgment under Uncertainty: Heuristics and Biases

Biases in judgments reveal some heuristics of thinking under uncertainty.

Amos Tversky and Daniel Kahneman

Many decisions are based on beliefs concerning the likelihood of uncertain events such as the outcome of an election, the guilt of a defendant, or the future value of the dollar. These beliefs are usually expressed in statements such as "I think that . . . ," "chances are . . . ," "it is unlikely that . . . ," and so forth. Occasionally, beliefs concerning uncertain events are expressed in numerical form as odds or subjective probabilities. What determines such beliefs? How do people assess the probability of an uncertain event or the value of an uncertain quantity? This article shows that people rely on a limited number of heuristic principles which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations. In general, these heuristics are quite useful, but sometimes they lead to severe and systematic errors.

The subjective assessment of probability resembles the subjective assessment of physical quantities such as distance or size. These judgments are all based on data of limited validity, which are processed according to heuristic rules. For example, the apparent distance of an object is determined in part by its clarity. The more sharply the object is seen, the closer it appears to be. This rule has some validity, because in any given scene the more distant objects are seen less sharply than nearer objects. However, the reliance on this rule leads to systematic errors in the estimation of distance. Specifically, distances are often overestimated when visibility is poor because the contours of objects are blurred. On the other hand, distances are often underestimated when visibility is good because the objects are seen sharply. Thus, the reliance on clarity as an indication of distance leads to common biases. Such biases are also found in the intuitive judgment of probability. This article describes three heuristics that are employed to assess probabilities and to predict values. Biases to which these heuristics lead are enumerated, and the applied and theoretical implications of these observations are discussed.

Representativeness

Many of the probabilistic questions with which people are concerned belong to one of the following types: What is the probability that object A belongs to class B? What is the probability that event A originates from process B? What is the probability that process B will generate event A? In answering such questions, people typically rely on the representativeness heuristic, in which probabilities are evaluated by the degree to which A is representative of B, that is, by the degree to which A resembles B. For example, when A is highly representative of B, the probability that A originates from B is judged to be high. On the other hand, if A is not similar to B, the probability that A originates from B is judged to be low.

For an illustration of judgment by representativeness, consider an individual who has been described by a former neighbor as follows: "Steve is very shy and withdrawn, invariably helpful, but with little interest in people, or in the world of reality. A meek and tidy soul, he has a need for order and structure, and a passion for detail." How do people assess the probability that Steve is engaged in a particular occupation from a list of possibilities (for example, farmer, salesman, airline pilot, librarian, or physician)? How do people order these occupations from most to least likely? In the representativeness heuristic, the probability that Steve is a librarian, for example, is assessed by the degree to which he is representative of, or similar to, the stereotype of a librarian. Indeed, research with problems of this type has shown that people order the occupations by probability and by similarity in exactly the same way (*1*). This approach to the judgment of probability leads to serious errors, because similarity, or representativeness, is not influenced by several factors that should affect judgments of probability.

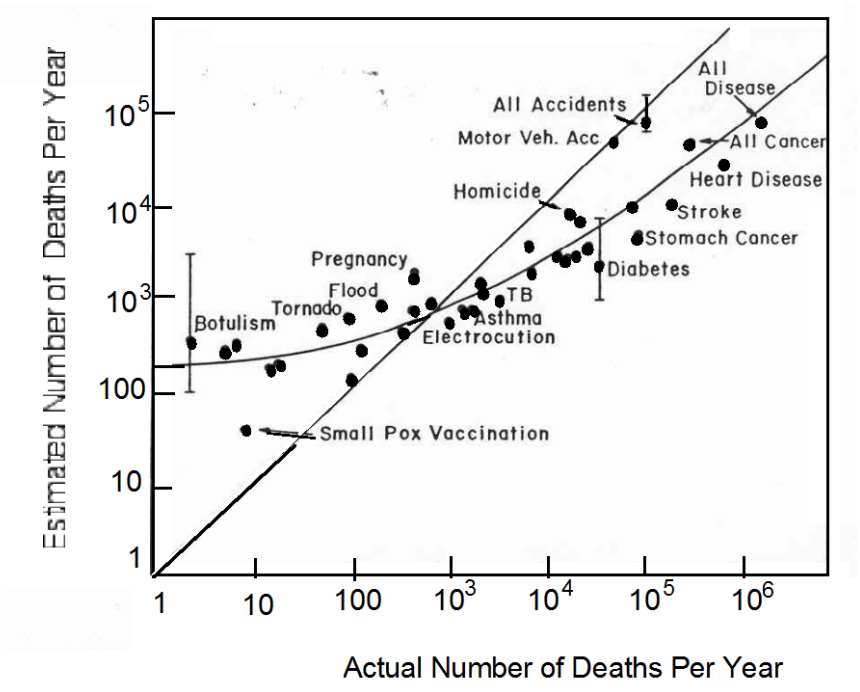
Insensitivity to prior probability of outcomes. One of the factors that have no effect on representativeness but should have a major effect on probability is the prior probability, or base-rate frequency, of the outcomes. In the case of Steve, for example, the fact that there are many more farmers than librarians in the population should enter into any reasonable estimate of the probability that Steve is a librarian rather than a farmer. Considerations of base-rate frequency, however, do not affect the similarity of Steve to the stereotypes of librarians and farmers. If people evaluate probability by representativeness, therefore, prior probabilities will be neglected. This hypothesis was tested in an experiment where prior probabilities were manipulated (*1*). Subjects were shown brief personality descriptions of several individuals, allegedly sampled at random from a group of 100 professionals—engineers and lawyers. The subjects were asked to assess, for each description, the probability that it belonged to an engineer rather than to a lawyer. In one experimental condition, subjects were told that the group from which the descriptions had been drawn consisted of 70 engineers and 30 lawyers. In another condition, subjects were told that the group consisted of 30 engineers and 70 lawyers. The odds that any particular description belongs to an engineer rather than to a lawyer should be higher in the first condition, where there is a majority of engineers, than in the second condition, where there is a majority of lawyers. Specifically, it can be shown by applying Bayes' rule that the ratio of these odds should be $(.7/.3)^2$, or 5.44, for each description. In a sharp violation of Bayes' rule, the subjects in the two conditions produced essen-

The authors are members of the department of psychology at the Hebrew University, Jerusalem, Israel.

1124 SCIENCE, VOL. 185

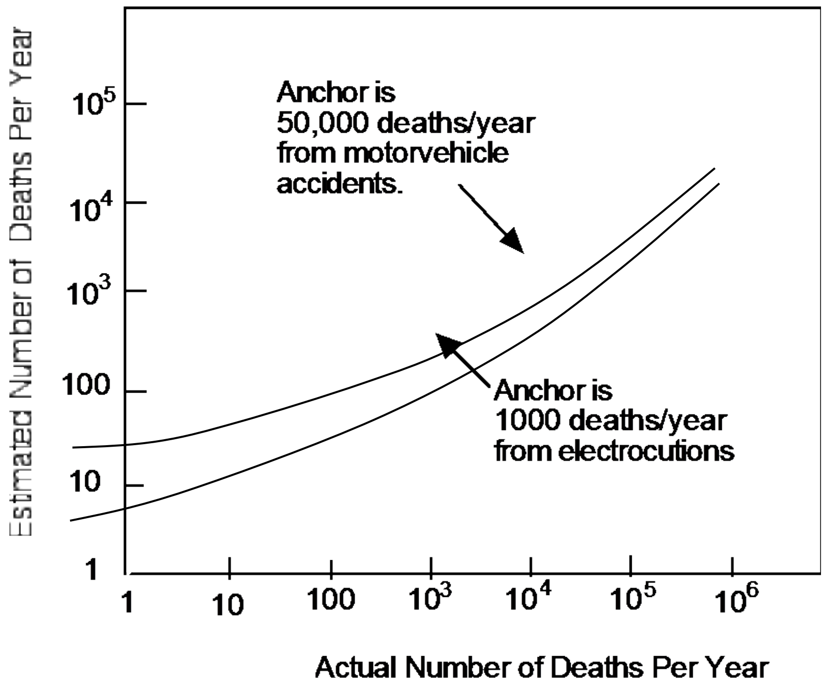
Examples of cognitive heuristics

Availability: probability judgment is driven by ease with which people can think of previous occurrences of the event or can imagine such occurrences.



Redrawen Lichtenstein, S., B. Fischhoff, and L.D. Phillips (1982) Calibration of probabilities: The state of the art to 1980," pp. 306-334 in D. Kahneman, P. Slovic, and A. Tversky (eds.), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press, 555pp.

Anchoring and adjustment: probability judgment is frequently driven by the starting point which becomes an "anchor."



As Scott Ferson noted yesterday, brain science is beginning to figure out where in the brain some of the relevant processes occur.

In this talk I will:

- Discuss *prescriptive* analytical strategies that suggest how people *should* frame and make decisions in the face of uncertainty.
    - Decision rules
    - Benefit-cost analysis
    - Decision analysis
    - Multi-criteria analysis
    - Real options
    - Bounding analysis

- Discuss how people *actually* frame and make decisions in the face of uncertainty.
    - Cognitive heuristics
    - Ubiquitous overconfidence
    - The need to be quantitative
    - Methods for formal quantitative expert elicitation
    - Problems with the use of scenarios
    - Two comments about integrated assessment.

Let’s try a demonstration:

I am going to name four canals.
I would like every one to write down three numbers

Your lower 1% estimate of the length of the canal
i.e., only 1 chance in 100 it could be shorter.

Your best estimate of the length of the canal.

Your upper 99% estimate of the length of the canal
i.e., only 1 chance in 100 it could be longer.

Here are the four canals:

Kile Canal

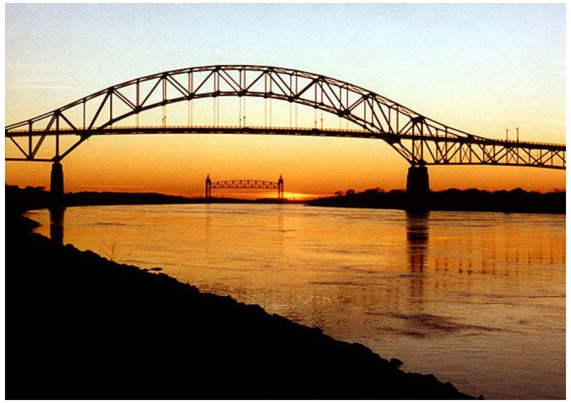
Between the North Sea
and the Baltic Sea

Suez Canal

Between the Mediterranean
and the Red Sea

Panama Canal

Between the Caribbean and the
Pacific Ocean



Cape Cod Canal

Between Cape Cod Bay and
Buzzards Bay

Here are the four canals:

95 km

Kile Canal

Between the North Sea
and the Baltic Sea

193 km

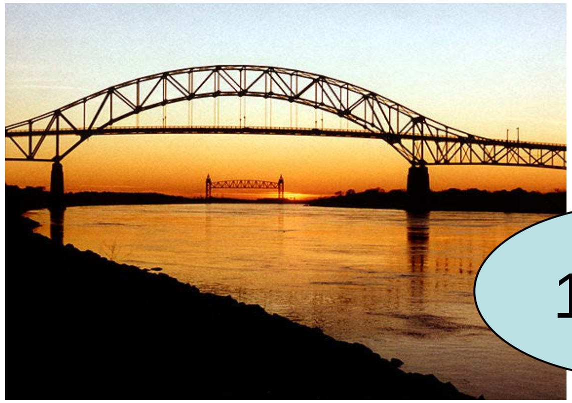
Suez Canal

Between the Mediterranean
and the Red Sea

82 km

Panama Canal

Between the Caribbean and the
Pacific Ocean

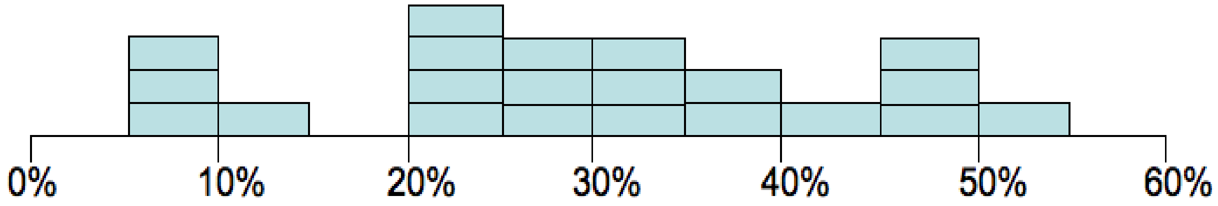


11km

Cape Cod Canal

Between Cape Cod Bay and
Buzzards Bay

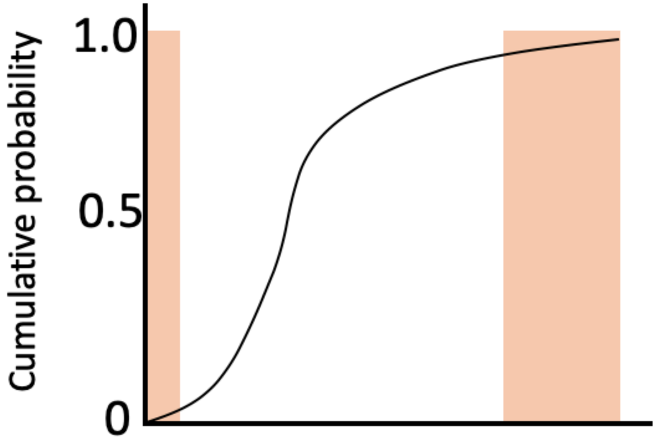
Over Confidence

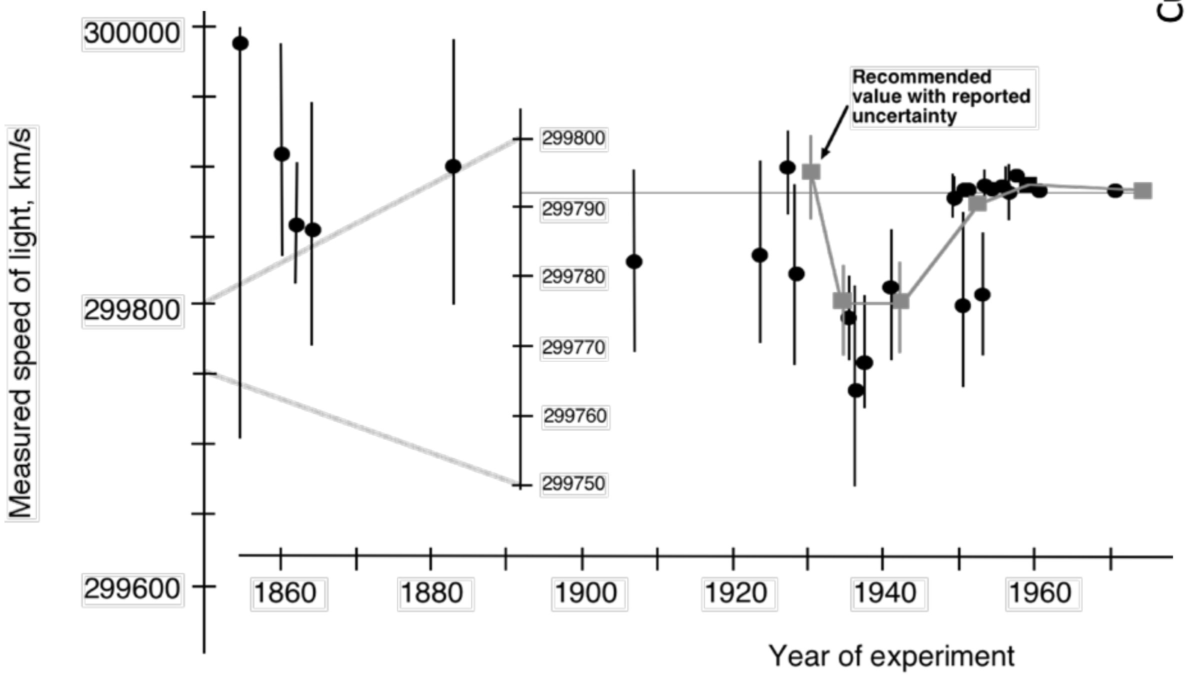


Percentage of estimates in which the true value lay outside of the respondent's assessed 98% confidence interval.

Source: Morgan and Henrion, 1990

Surprise index: Should be 2%. The probability that the true value lies below the 1% lower bound or above the 99% upper bound





For details see: Henrion and Fischhoff, "Assessing Uncertatinty in Physical Constants," *American Journal of Physics*, 54, pp791-798, 1986.

In this talk I will:

- Discuss *prescriptive* analytical strategies that suggest how people *should* frame and make decisions in the face of uncertainty.
  - Decision rules
  - Benefit-cost analysis
  - Decision analysis
  - Multi-criteria analysis
  - Real options
  - Bounding analysis

- Discuss how people *actually* frame and make decisions in the face of uncertainty.
  - Cognitive heuristics
  - Ubiquitous overconfidence
  - The need to be quantitative
  - Methods for formal quantitative expert elicitation
  - Problems with the use of scenarios
  - Two comments about integrated assessment.

Yesterday…

…Karl Teigen talked at length about the problems associated with using probability words to support decision making.

As he noted, such words can mean very different things in different circumstances and different things to different people in the same circumstance.

I can illustrate with an example from the U.S. EPA's Science Advisory Board

The SAB was discussing…

…words to use to describe whether a substance is or is not a likely carcinogen.

The minimum probability associated with the word "likely" spanned four orders of magnitude.

The maximum probability associated with the word "not likely" spanned more than five orders of magnitude.

There was an overlap of the probability associated with the word "likely" and that associated with the word "unlikely"!

Figure from: M. Granger Morgan, "Uncertainty Analysis in Risk Assessment," *Human and Ecological Risk Assessment*, *4*(1), 25-39, February 1998.

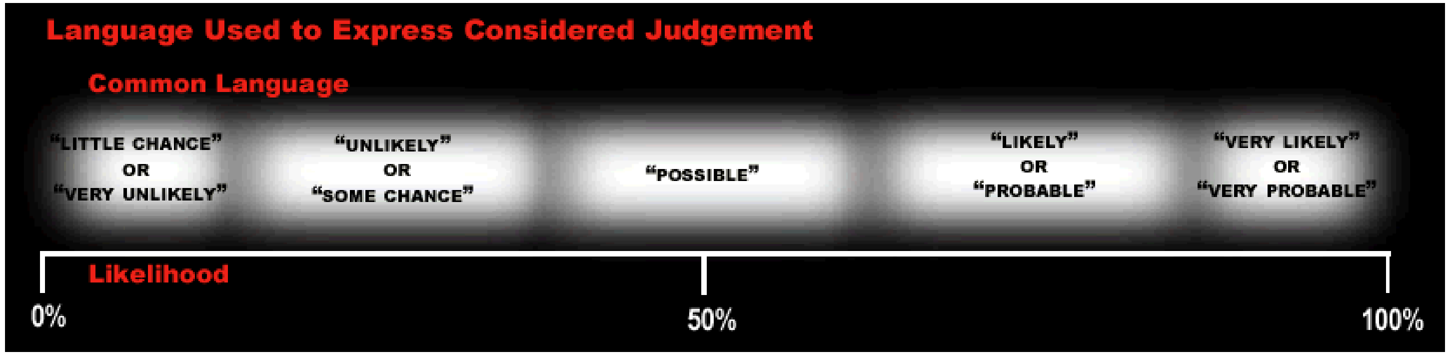
Words are not enough…(Cont.)

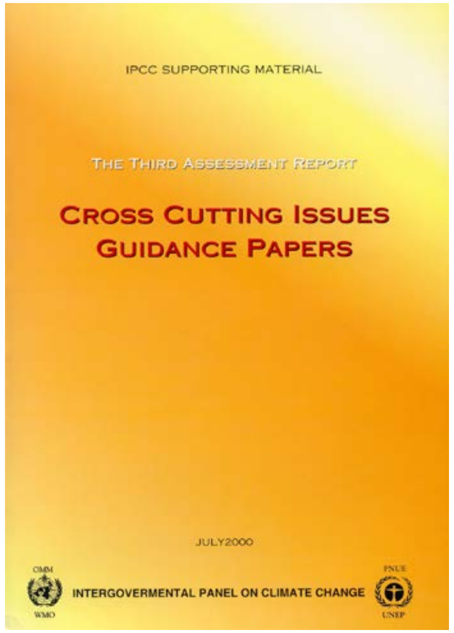
Without some quantification, qualitative descriptions of uncertainty convey little, if any, useful information to decision makers.

The climate assessment community is gradually learning this lesson.

Steve Schneider and Richard Moss worked hard to promote a better treatment of uncertainty by the IPCC.

At my insistence, the first U.S. National Climate Assessment Synthesis Team gave quantitative definitions to five probability words:





Mapping of probability words into quantitative subjective probability judgments, used by WG I and II of the IPCC Third Assessment (2001) based on recommendations developed by Moss and Schneider (2000).

word	probability range
Virtually certain	> 0.99
Very likely	0.9-0.99
Likely	0.66-0.9
Medium likelihood	0.33-0.66
Unlikely	0.1-0.33
Very unlikely	0.01-0.1
Exceptionally unlikely	< 0.01

Note: The report of the *IPCC Workshop on Describing Scientific Uncertainties in Climate Change to Support Analysis of Risk and of Options* (2004) observed: "Although WGIII TAR authors addressed uncertainties in the WG3-TAR, they did not adopt the Moss and Schneider uncertainty guidelines. The treatment of uncertainty in the WG3-AR4 can be improved over what was done in the TAR."

Many other communities have not yet gotten the message

In this talk I will:

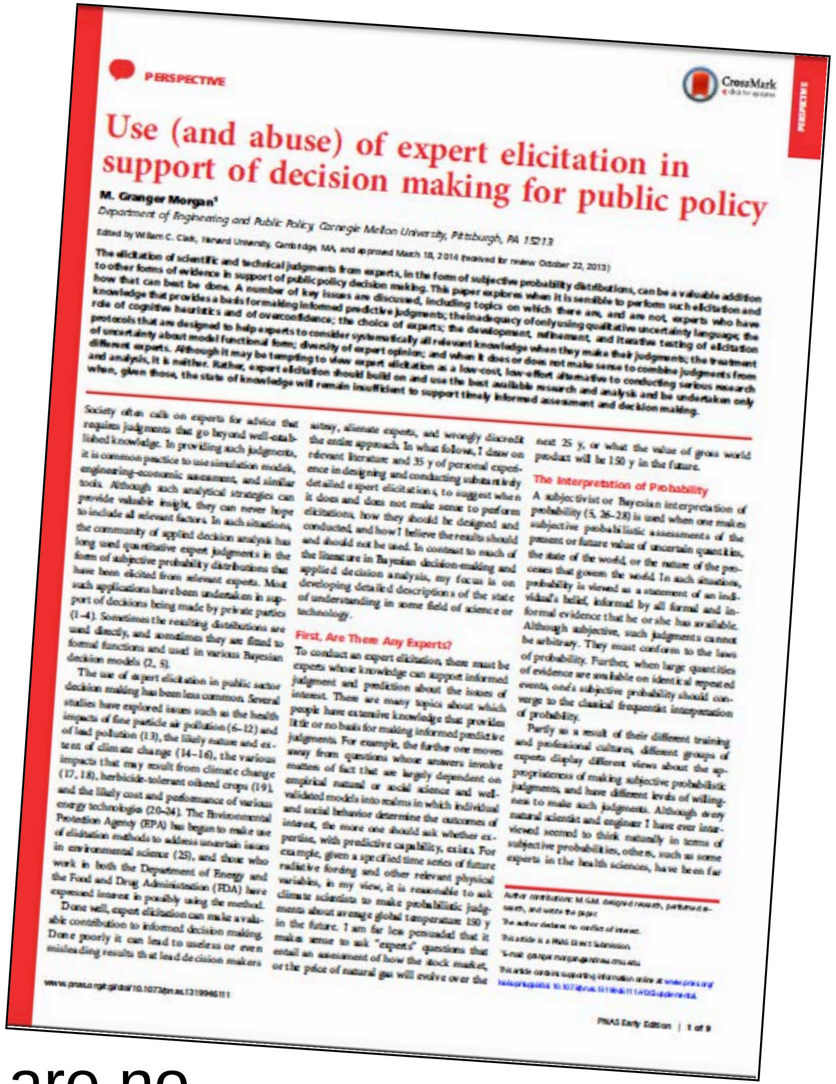
- Discuss *prescriptive* analytical strategies that suggest how people *should* frame and make decisions in the face of uncertainty.
  - Decision rules
  - Benefit-cost analysis
  - Decision analysis
  - Multi-criteria analysis
  - Real options
  - Bounding analysis

- Discuss how people *actually* frame and make decisions in the face of uncertainty.
  - Cognitive heuristics
  - Ubiquitous overconfidence
  - The need to be quantitative
  - Methods for formal quantitative expert elicitation
  - Problems with the use of scenarios
  - Two comments about integrated assessment.

Expert elicitation

Eliciting probabilistic judgments from experts requires careful preparation and execution.

Developing and testing an appropriate interview protocol typically takes several months. Each interview is likely to require several hours.


PERSPECTIVE

Use (and abuse) of expert elicitation in support of decision making for public policy

M. Granger Morgan[1]

Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA 15213

When addressing complex, scientifically subtle questions of the sorts involved with problems like climate change, there are no satisfactory short cuts. Attempts to simplify and speed up the process almost always lead to shoddy results.

I’ve done a bunch of expert elicitations

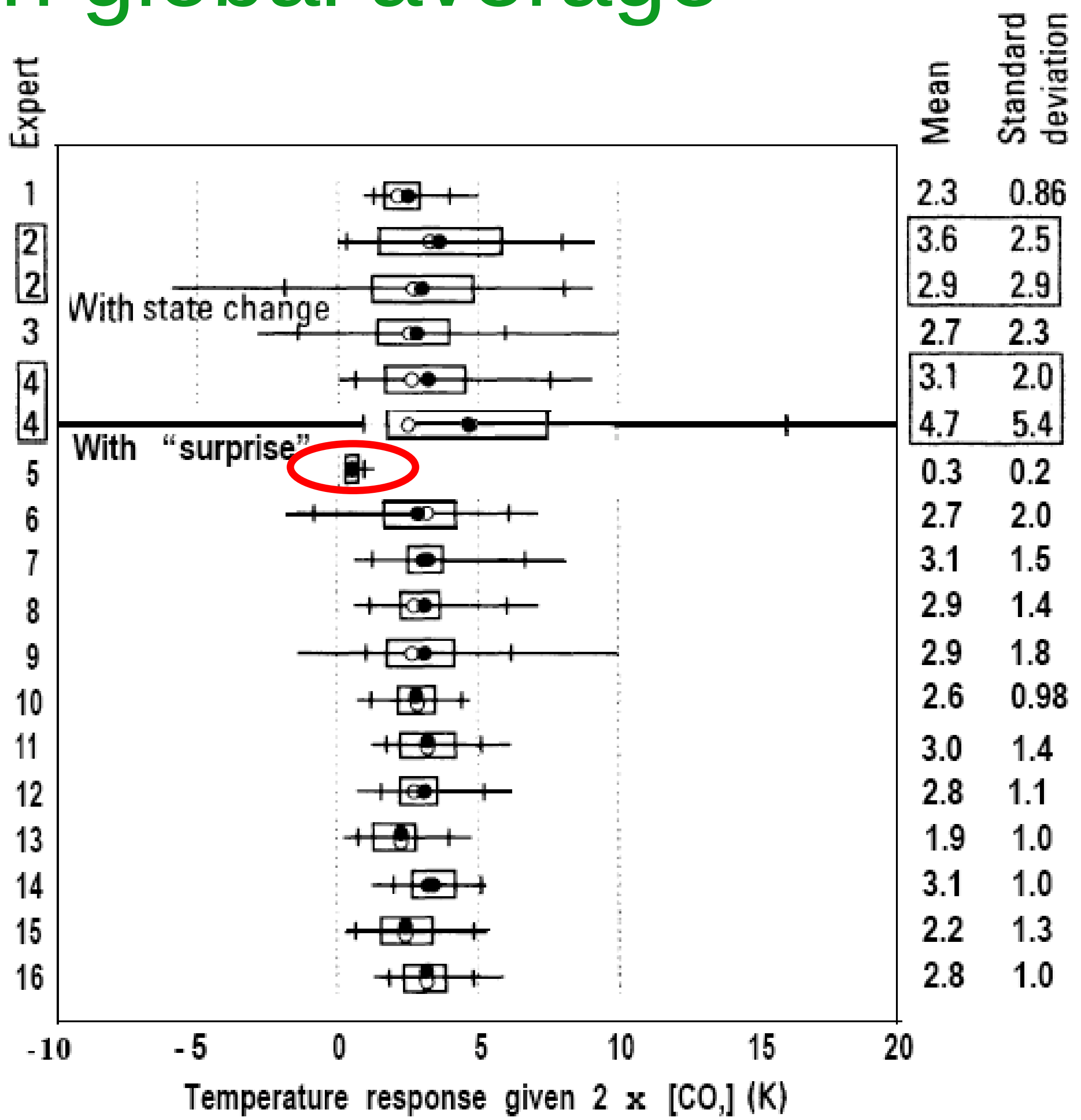
While I was going to talk about a couple I’ve decided instead to offer just three insights on:

- Motivational bias;
- Individual elicitation *versus* group consensus;
- Combing experts – and situations where different experts have different view about of how the world works.

When we did it.	**Topics we asked about.**	**Reference at the end of this chapter to the paper we published that describes the results.**
1980-1	Interviews with 9 air pollution experts and with 7 health experts to better understand and model the health impacts of the sulfur air pollution that comes from power plants that burn coal.	Morris, Henrion, Amaral and Rish, (1984); Morgan, Morris, Henrion and Amaral (1985).
1993-4	Interviews with 16 leading U.S. climate scientists to ask about how much warming may happen and other uncertainties in climate science.	Morgan and Keith (1994)
1999-2000	Interviews with 11 leading forest experts (and 5 biodiversity experts) to ask about the impacts that climate change may have on tropical and northern forests.	Morgan, Pitelka and Shevlikova (2001)
2005-6	Interviews with 12 leading oceanographers and climate scientists to ask about how climate change may influence the circulation of water and heat in the Atlantic Ocean.	Zickfeld, Levermann, Kuhlbrodt. Rahmstorf, Morgan and Keith (2007)
2005-6	Survey of 24 leading atmospheric and climate scientists to explore how the direct and indirect ways in which high-altitude small particles in the atmosphere warm or cool the planet.	Morgan, Adams, Keith (2006)
2006-7	Interviews with 18 experts about conventional and advanced technology for solar cells to explore how cost and performance may change over time.	Courtright, Morgan, Keith (2008)
2008-9	Interviews with 14 leading U.S. climate scientists (four who were the same as in the earlier study) to ask about how warming will change over time and about other uncertainties in climate science.	Zickfeld, Morgan, Frame and Keith (2010)
2011-12	Interviews with 16 nuclear engineers about how the cost and future performance of small modular nuclear reactors (MRs) are likely to compare with the cost of existing large reactors.	Abdulla, Azevedo and Morgan (2013)

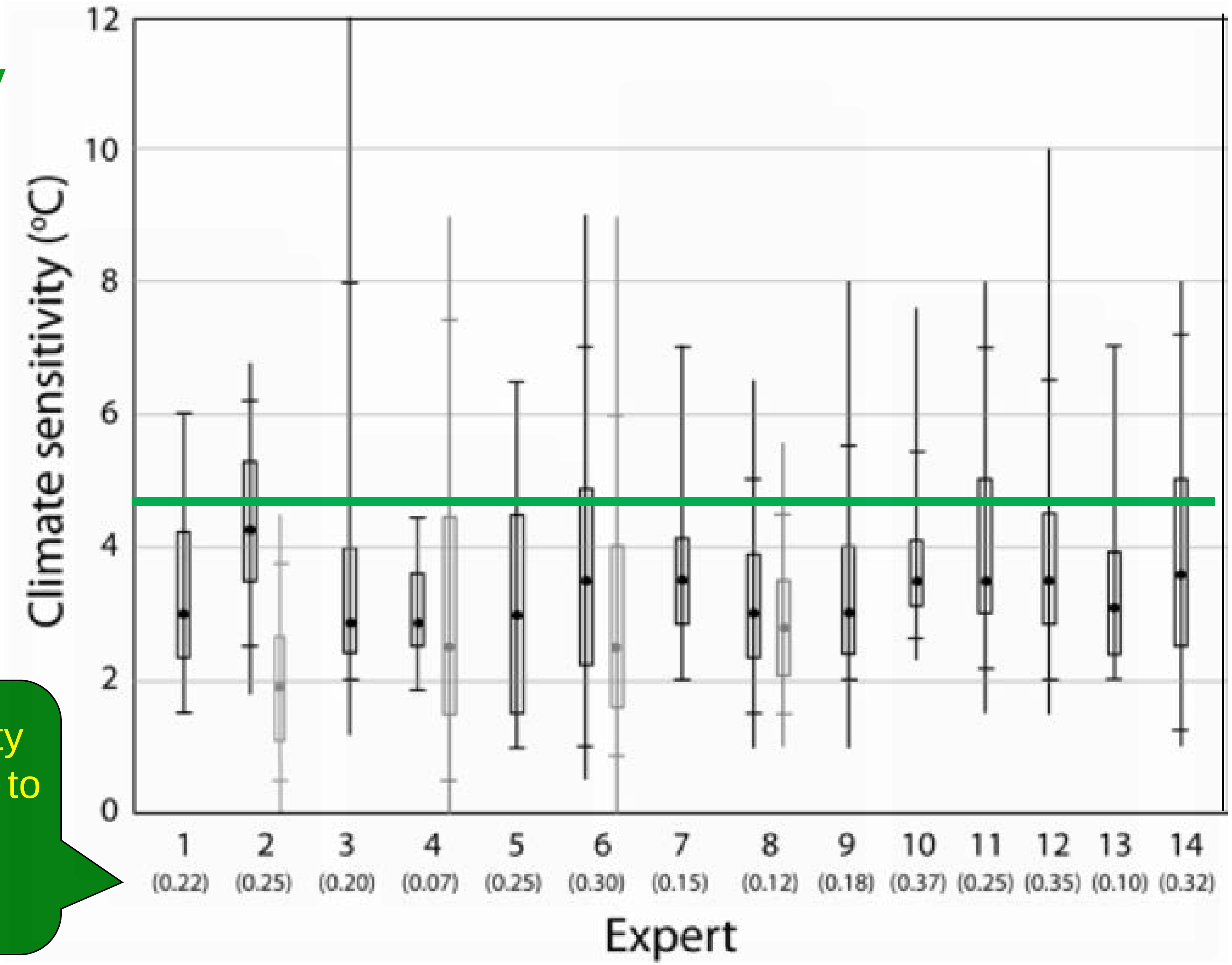
Equilibrium change in global average temperature

200 years after a $2xCO_2$ change



M. Granger Morgan and David Keith, "Subjective Judgments by Climate Experts," *Environmental Science & Technology*, *29*(10), 468A-476A, October 1995.

Climate sensitivity

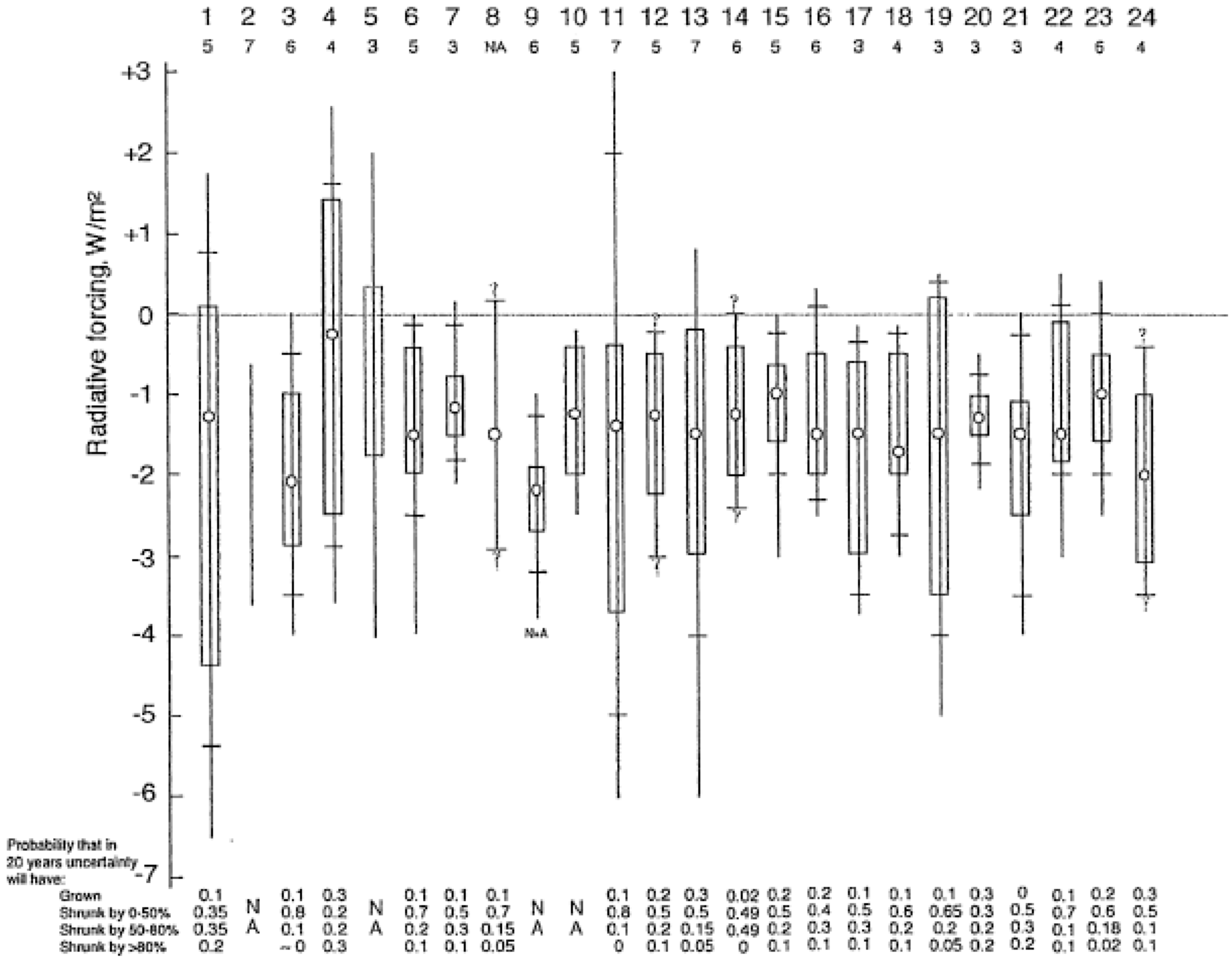


Probability allocated to values above 4.5° C

Kirsten Zickfeld, M. Granger Morgan, David Frame and David W. Keith, "Expert Judgments About Transient Climate Response to Alternative Future Trajectories of Radiative Forcing," *Proceedings of the National Academy of Sciences*, *107*, 12451-12456, July 13, 2010.

Total aerosol forcing

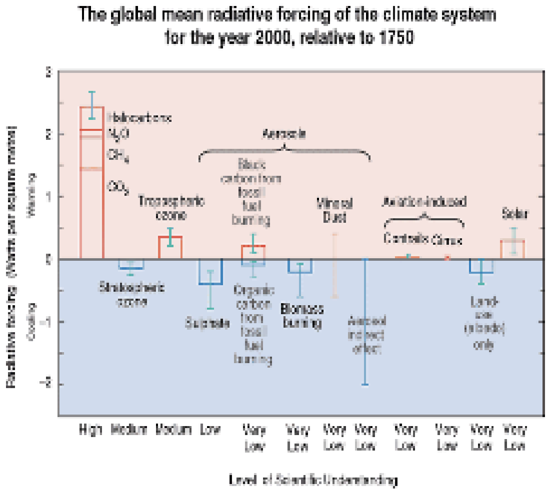
(at the top of the atmosphere)



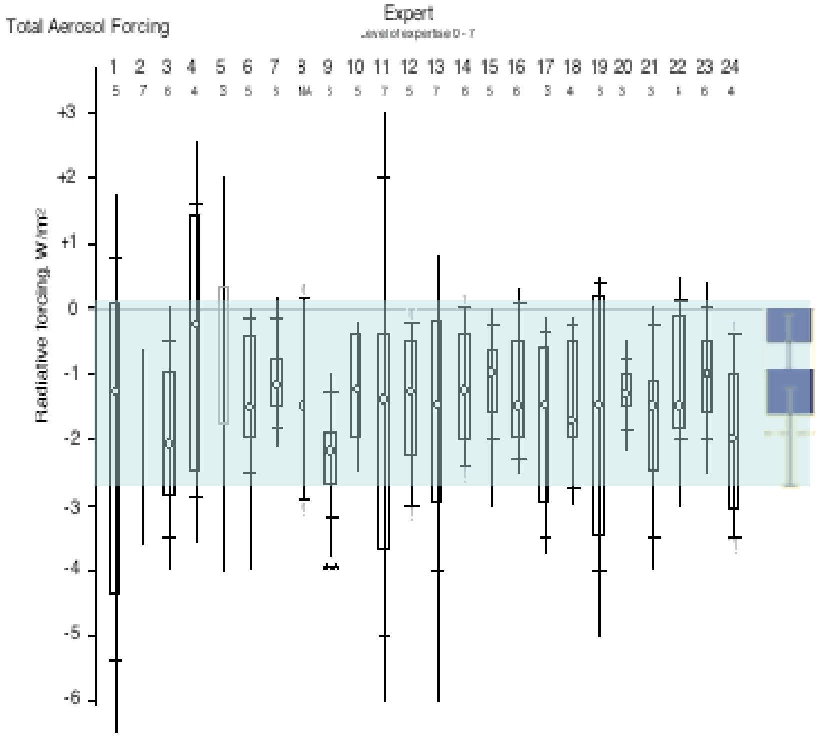
M. Granger Morgan, Peter Adams, and David W. Keith, "Elicitation of Expert Judgments of Aerosol Forcing," *Climatic Change*, *75*, 195-214, 2006.

Comparison with IPCC 4th assessment consensus results

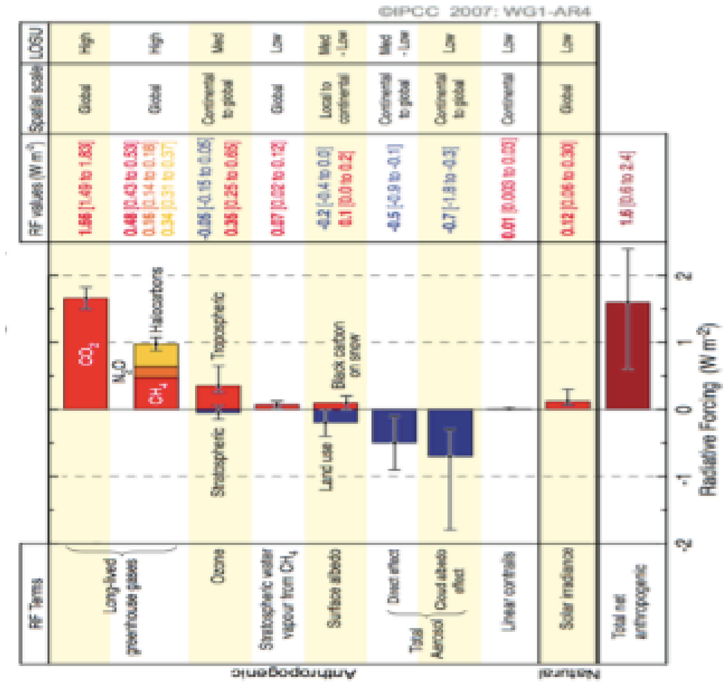
Summary from TAR



Total aerosol forcing from Morgan, Adams and Keith

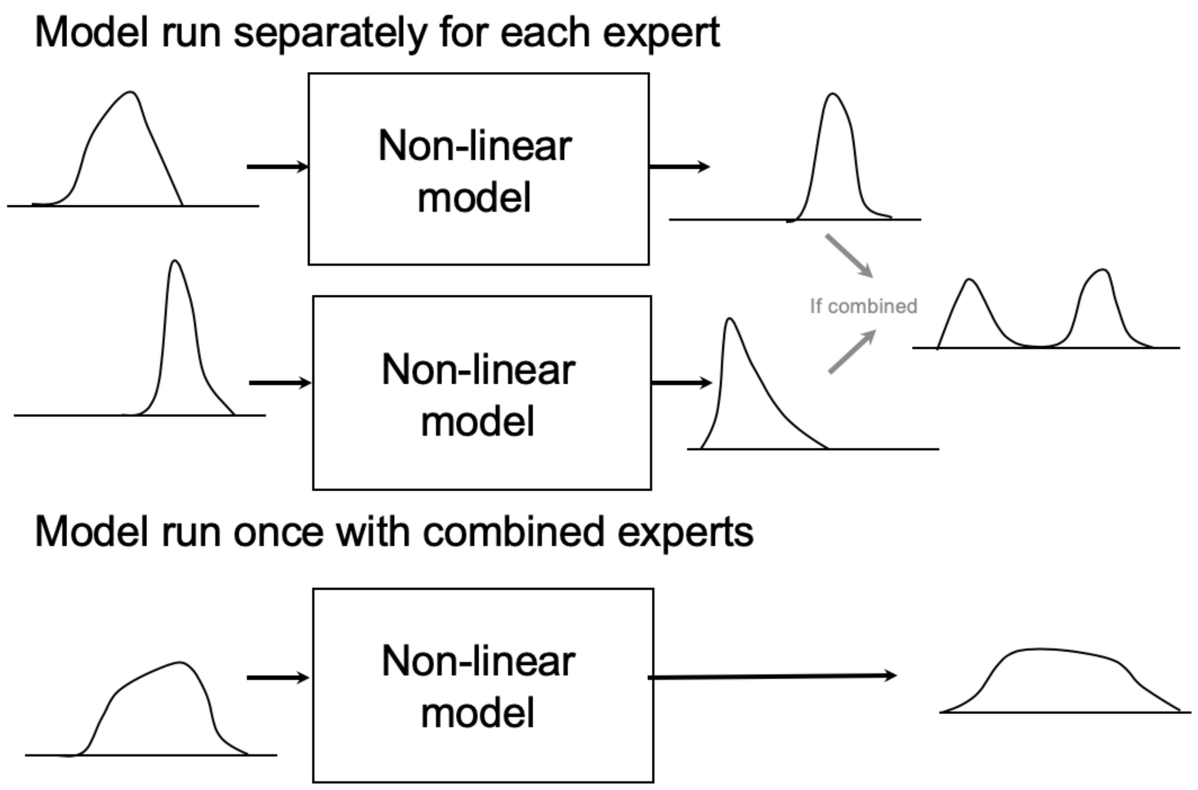


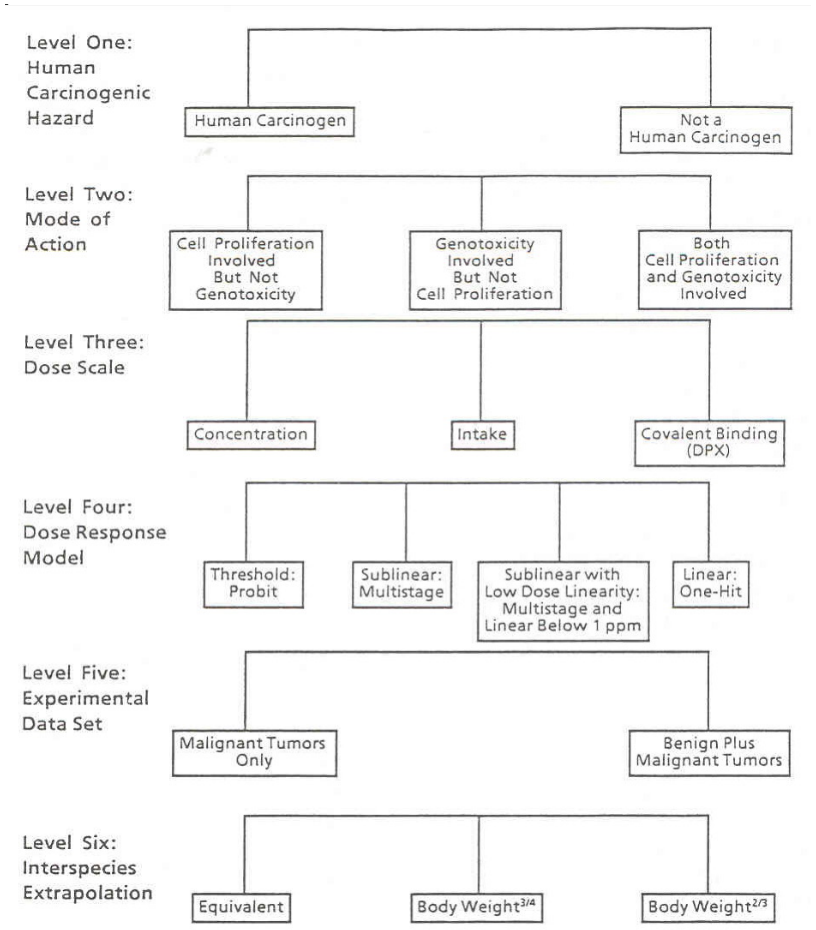
Summary from FR4



IPCC reports are available at www.IPCC.ch

Different experts have different views of how the world works





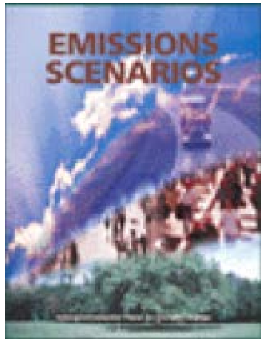
For details see: John S. Evans et al., "A distributional approach to characterizing low-dose cancer risk," *Risk Analysis, 14*, 25-34, 1994; and John S. Evans et al., "Use of probabilistic expert judgment in uncertainty analysis of carcinogenic potency," *Regulatory Toxicology and Pharmacology*, *20*, 15-36, 1994.

In this talk I will:

- Discuss *prescriptive* analytical strategies that suggest how people *should* frame and make decisions in the face of uncertainty.
    - Decision rules
    - Benefit-cost analysis
    - Decision analysis
    - Multi-criteria analysis
    - Real options
    - Bounding analysis

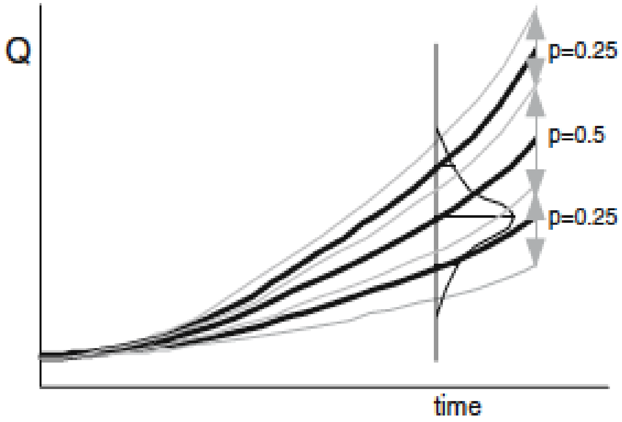
- Discuss how people *actually* frame and make decisions in the face of uncertainty.
    - Cognitive heuristics
    - Ubiquitous overconfidence
    - The need to be quantitative
    - Methods for formal quantitative expert elicitation
    - Problems with the use of scenarios
    - Two comments about integrated assessment.

Scenarios are widely used



For example, the previous IPCC assessment made use of the very detailed SRES scenarios in making its projections.

While in principle there are ways to create scenarios that span ranges across the space of plausible futures, this is very rarely done.



Folks who construct scenarios often argue that they should not be viewed as "predictions" but rather as a strategy to help people think about how things might unfold in the future.

But, there is a problem with this argument…

SRES is at: www.ipcc.ch/ipccreports/sres/emission/index.php?idp=0

Again, from the work of Tversky and Kahneman

Tom W. is of high intelligence, although lacking in true creativity. He has a need for order and clarity, and for neat and tidy systems in which every detail finds its appropriate place. His writing is rather dull and mechanical, occasionally enlivened by somewhat corny puns and by flashes of imagination of the sci-fi type. He has a strong drive for competence. He seems to have little feel and little sympathy for other people and does not enjoy interacting with others.

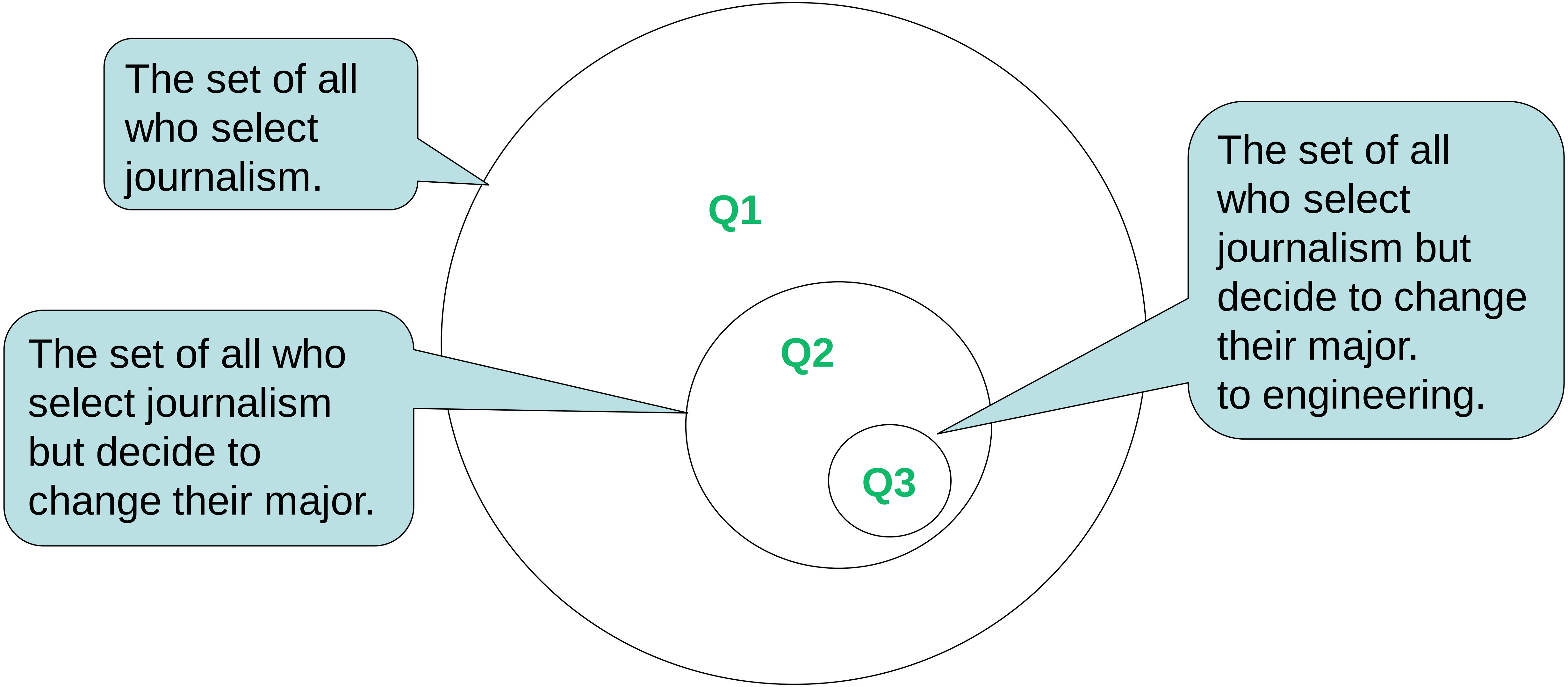
Group 1 got Q1: What is the probability that Tom W. will select journalism as his major in college?

Group 2 got Q2: What is the probability that Tom W. will select journalism as his major in college but decide he does not like it and decide to change his major?

Group 3 got Q3: What is the probability that Tom W. will select journalism as his college major but become unhappy with his choice and switch to engineering?

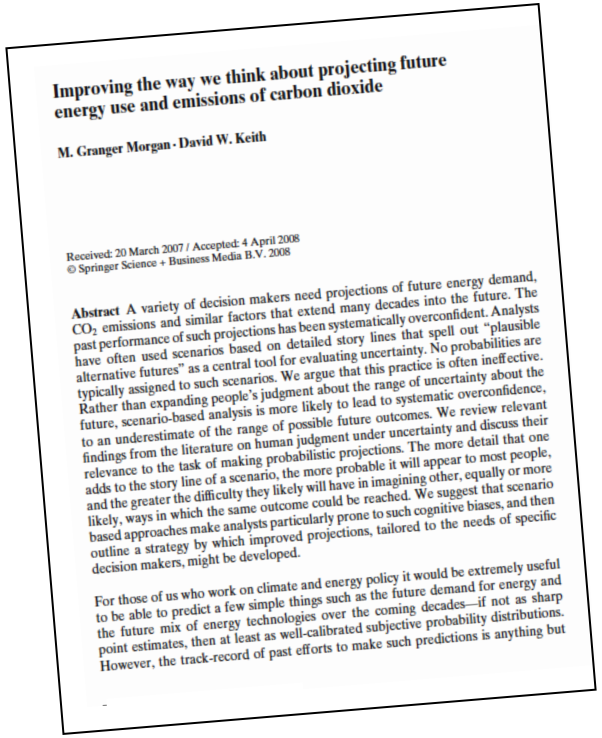
Assessed probabilities went ***up*** but should have gone down.

All people who fit…



The more detail…

…that gets added to the “story line” of a scenario, the harder people find it to remember that there are typically many other ways that one could reach the same outcome, as well as many other possible outcomes that could result - this is because of the heuristic of “availability.”



Improving the way we think about projecting future energy use and emissions of carbon dioxide

M. Granger Morgan · David W. Keith

Received: 20 March 2007 / Accepted: 4 April 2008

Abstract A variety of decision makers need projections of future energy demand, CO_2 emissions and similar factors that extend many decades into the future. The past performance of such projections has been systematically overconfident. Analysts have often used scenarios based on detailed story lines that spell out “plausible alternative futures” as a central tool for evaluating uncertainty. No probabilities are typically assigned to such scenarios. We argue that this practice is often ineffective. Rather than expanding people’s judgment about the range of uncertainty about the future, scenario-based analysis is more likely to lead to systematic overconfidence, to an underestimate of the range of possible future outcomes. We review relevant findings from the literature on human judgment under uncertainty and discuss their relevance to the task of making probabilistic projections. The more detail that one adds to the story line of a scenario, the more probable it will appear to most people, and the greater the difficulty they likely will have in imagining other, equally or more likely, ways in which the same outcome could be reached. We suggest that scenario based approaches make analysts particularly prone to such cognitive biases, and then outline a strategy by which improved projections, tailored to the needs of specific decision makers, might be developed.

For those of us who work on climate and energy policy it would be extremely useful to be able to predict a few simple things such as the future demand for energy and the future mix of energy technologies over the coming decades—if not as sharp point estimates, then at least as well-calibrated subjective probability distributions. However, the track-record of past efforts to make such predictions is anything but

For additional elaboration of this and related arguments, and some suggestions for how to improve on past practice, see:

M. Granger Morgan and David Keith, "Improving the Way We Think About Projecting Future Energy Use and Emissions of Carbon Dioxide," *Climatic Change*, *90*(3), 189-215, October 2008.

My concern with scenarios is well illustrated…

…by a quotation from a book by W.L. Gregory (2001) promoting the use of scenarios who argues:

> Practitioners can find several advantages in using scenarios. First, they can use scenarios to enhance a person's or group's expectancies that an event will occur. This can be useful for gaining acceptance of a forecast. . . Second, scenarios can be used as a means of decreasing existing expectancies. . . .Third. . . scenarios can produce greater commitment in the clients to taking actions described in them.

Gregory, R. (2001). "Scenarios and Acceptance of Forecasts." in J.S. Armstrong (ed.), *Principles of Forecasting: A Handbook for Researchers and Practitioners*, Kluwer, 849pp.

In this talk I will:

- Discuss *prescriptive* analytical strategies that suggest how people *should* frame and make decisions in the face of uncertainty.
  - Decision rules
  - Benefit-cost analysis
  - Decision analysis
  - Multi-criteria analysis
  - Real options
  - Bounding analysis
- Discuss how people *actually* frame and make decisions in the face of uncertainty.
  - Cognitive heuristics
  - Ubiquitous overconfidence
  - The need to be quantitative
  - Methods for formal quantitative expert elicitation
  - Problems with the use of scenarios
  - Two comments about integrated assessment.

Comparison of two approaches to integrated assessment models to support decisions about climate change

DICE

Dynamic Integrated Climate-Economy model.

Bill Nordhaus et al.

ICAM

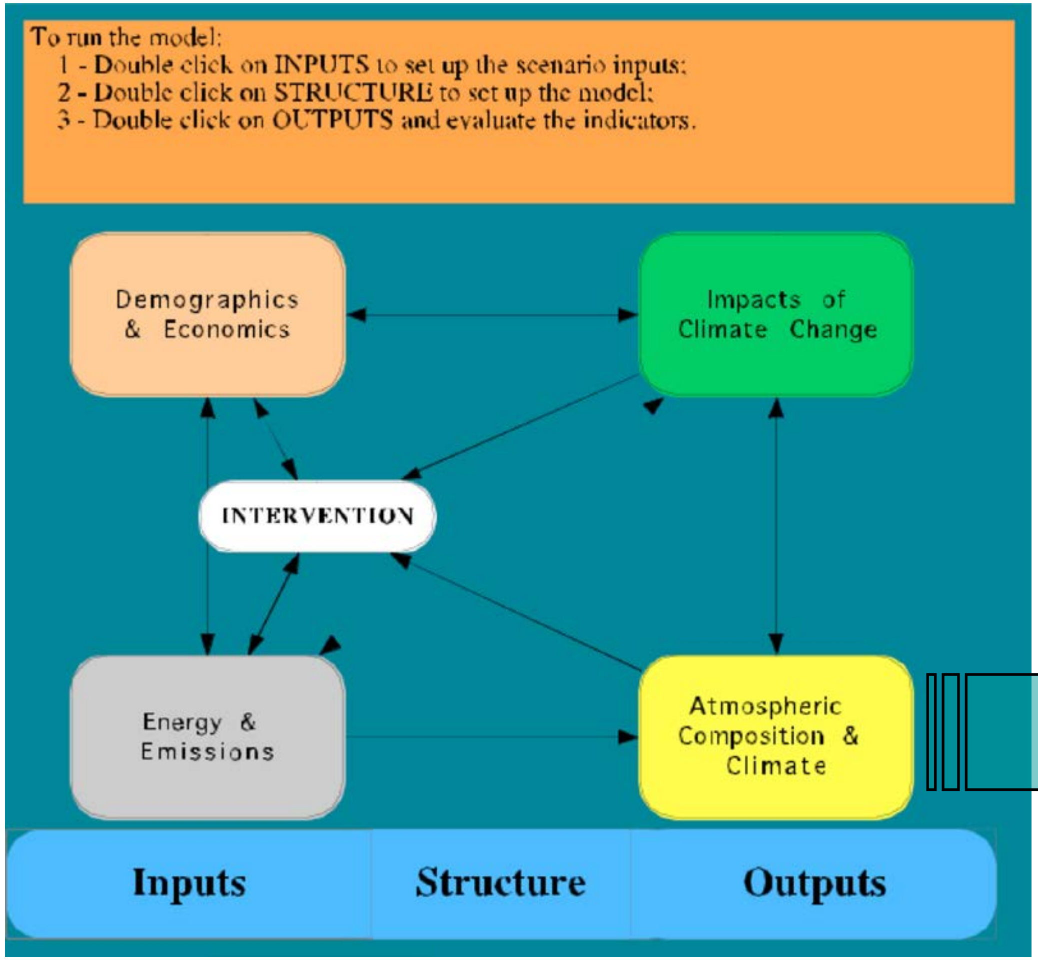
Integrated climate assessment model.

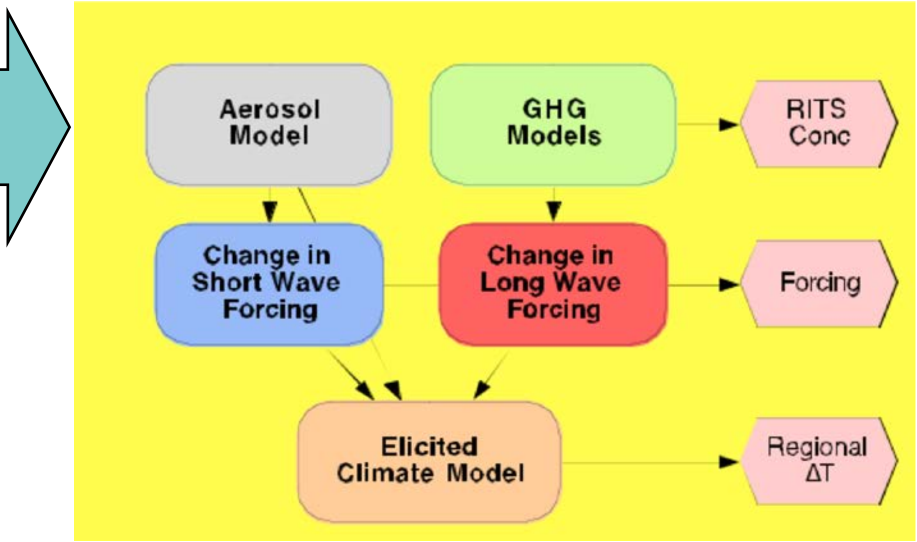
Hadi Dowlatabadi et al.

ICAM

Integrated Climate
Assessment Model

A very large hierarchically organized stochastic simulation model built in Analytica®.





See for example:
Hadi Dowlatabadi and M. Granger Morgan, "A Model Framework for Integrated Studies of the Climate Problem," *Energy Policy*, *21*(3), 209-221, March 1993.
and
M. Granger Morgan and Hadi Dowlatabadi, "Learning from Integrated Assessment of Climate Change," *Climatic Change*, *34*, 337-368, 1996.

ICAM was focused on…

…doing a good job of dealing with uncertainty.

It treats all important coefficients as full probability distributions and produces results that are PDFs.

It contains switches that allow the user to use a variety of different functional forms.

We found that:

- One could get a large variety of answers depending on how the model was structured.
- In light of this, we concluded that global integrated assessment models that do optimization, using just one assumed structure, make absolutely no sense.

So…while others continue to build optimizing IA models, we now just focus on how to reduce GHG emissions. See: CEDMCenter.org

Incidentally, on the subject of model and parameter uncertainty…

…Ullrika Sahlin and I have been having fun discussing types of uncertainty.

In my recent book on theory and practice in policy analysis I wrote

Much of the literature divides uncertainty into two broad categories, termed opaquely (for those of us who are not Latin scholars) *aleatory* uncertainty and *epistemic* uncertainty. As Paté-Cornell (1996) explains, aleatory uncertainty stems "…from variability in known (or observable) populations and, therefore, represents randomness" while epistemic uncertainty "…comes from basic lack of knowledge about fundamental phenomena (…also known in the literature as ambiguity)."

While this distinction is common in the more theoretical literature, I believe that it is of limited utility in the context of applied problems involving assessment and decision making in technology and public policy where most key uncertainties involve a combination of the two.

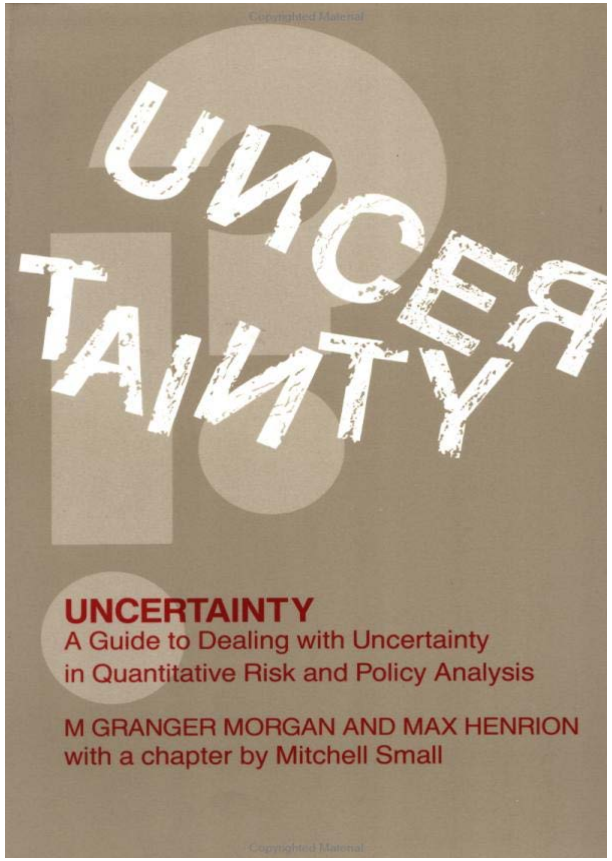
A far more useful categorization for our purposes is the split between "uncertainty about the value of empirical quantities" and "uncertainty about model functional form." The first of these may be either aleatory (the top wind speed that occurred in any Atlantic hurricane in the year 1995) or epistemic (the average global radiative forcing produced by anthropogenic aerosols at the top of the atmosphere during 1995). There is some disagreement within the community of experts about whether it is even appropriate to use the terms epistemic or aleatory when referring to a model. The Random House Dictionary defines *aleatory* as "of or pertaining to accidental causes; of luck or chance; unpredictable" and defines *epistemic* as "of or pertaining to knowledge or the conditions for acquiring it."

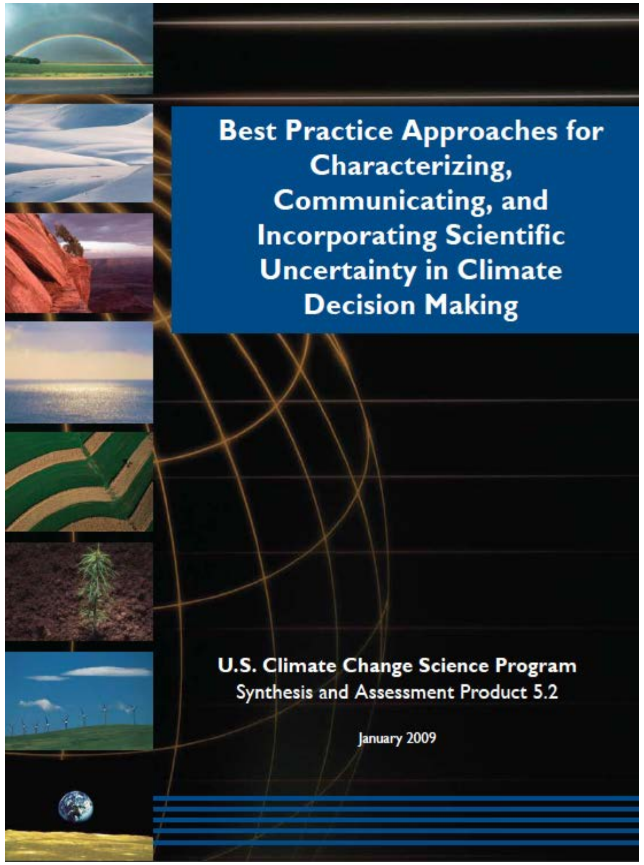
Five bottom lines

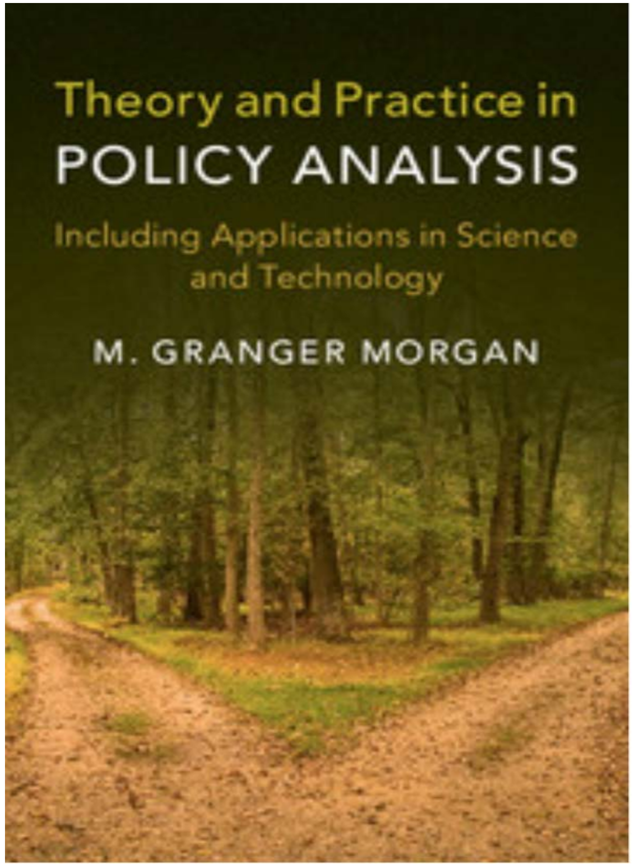
1. Uncertainty is present in virtually all important decisions.
2. We make decisions in the face of such uncertainty all the time.
3. Our mental capabilities are limited when it comes to assessing and dealing with uncertainty.
4. Hence, especially for important decisions, we should seek help in making such decisions.
5. There are a wide variety of formal analytical strategies, such as decision analysis, that can be very helpful in providing insight and guidance when we need to make important decisions in the presence of uncertainty.

Finally I have written…

…quite a bit on how to incorporate many of these ideas into policy analysis. For example:







M. Granger Morgan, Max Henrion, with Mitchell Small, *Uncertainty: A guide to dealing with uncertainty in quantitative risk and policy analysis,* 332pp., Cambridge University Press, New York, 1990. (Paperback edition 1992. *Best Practice Approaches for Characterizing, Communicating, and Incorporating Scientific Uncertainty in Decision-making*. [M. Granger Morgan (Lead Author), Hadi Dowlatabadi, Max Henrion, David Keith, Robert Lempert, Sandra McBride, Mitchell Small, and Thomas Wilbanks (Contributing Authors)]. A Report by the Climate Change Science Program and the Subcommittee on Global Change Research. National Oceanic and Atmospheric Administration, Washington, DC, 96pp., 2009.
Granger Morgan, *Theory and Practice in Policy Analysis: Including applications in science and technology*, Cambridge University Press, 590pp., 2017.

Acknowledgments

Most of the specific examples I have presented are drawn from work that has been supported by NSF.

This includes support under SBR-9521914, SES-8715564, SES-9309428, SES-9209940, SES-9209553, SES-9975200 and support through the Center for the Integrated Assessment of Global Change (SES-9022738), the Climate Decision Making Center (SES-0345798) and the Center for Climate and Energy Decision Making (SES-0949710) operated through cooperative agreements between the National Science Foundation and Carnegie Mellon University. Support has also come from EPRI under contracts RP 2955-3, 2955-10, 2955-11, and EP-P26150C12608 as well as from Carnegie Mellon University and several other sources.